# AI-based Frame work for IoT based Sensor Networks and 5G Integrated Spectrum Selection and Spectrum Access

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**Abstract:** The convulsion of multi-entry multi-output and ultra-dense networks was commonly regarded as the main facilitators to promote the creation and establishment of 5G systems. The exponential growth of wireless devices involves the use of Internet of Things (IoT), the potential that wireless communications will interconnect diversified things. Artificial Intelligence (AI) plays an important role in the 5G network to allow wireless connectivity to IoT users. Although current end-to-end learning and adaptive model need continuous monitoring and complex adjustments due to wireless signal classificators are unable to achieve global optimisation. More intrusion and more. In this paper an optimised range of spectrum and access to spectrums through a greedy AI-based architecture is presented to satisfy the upcoming requirements for 5Gs and beyond. A fractional Greedy approach is implemented and the Langrange Hyperplane approach is used to incorporate AI-based strategies to pick spectrum and assign spectrum for IoT-capable sensor systems. This system is referred to as the Langrange and Fractional Knapsack Hyperspectrum Access (FK-LHSA). The FKMSS model is developed in conjunction with an energy consumption model to optimise the channel. Or throughput of spectrum. Next, the spectrum access model of the LagrangeHyperflugzeug (LH) is designed to reduce speed delay and increase the accuracy of spectrum access. The results of the simulation show that the proposed FKM and LH models will minimise the access time and increase the accuracy of throughput and spectrum.

**Keywords**

Internet of things, Spectrum selection, Spectrum allocation, Artificial intelligence, Fractional Knapsack, Lagrange hyper plane.

## 1. Introduction

The Fifth-Generation (5G) Internet of Things (IoT) system has higher storage bandwidth and reduced power. For heterogeneous wireless users or machine computers, IoT networks are used. The number of users' spectrum use is increased in wireless networks. AI-based methods are used to handle the management of resources across a wide number of 5G network devices. In recent years, wireless communication have made fair improvement. The rising number of different types of wireless appliances are some trends with the increasing demand for spectrum. But the spectrum is an insignificant resource. Because of this, some spectrum elements are purposely used, while others are severely underused. It is undeniably necessary for 5G to increase and balance spectrum use through controlling spectrum and access to spectrum. However, in such a complicated world, spectrum monitoring and access to spectrum require distributed sensing over a wide range of frequency and result in spectrum data flooding. Earlier part learning is now practiced instantly by using simple wireless connection displays. No hand-designed expert features were needed when unique models of spectrum access demanded cyclical patterns based on higher order factors. The trained approach also removed the need for complicated machine-learning system by the wireless signal categorizer. Thereby the design of wireless signal classificatory has been systematically presented as a computational framework for end-to-end learning, including spectrum control and access to the device.

The accuracy of the system and the true positive rate have therefore been changed and the classification efficiency has therefore been considerably increased. However, since technologies are heterogeneous and operate in several radio bands, the multiple front bands generated from IoT devices require constantly monitoring that the size and speed of radio spectrum data exceed many orders of magnitude compared to traditional data collected on other wireless sensor networks (e.g. temperature, humidity reports, etc.). This high data volume resulting from IoT devices can be managed and the entire spectrum can be optimally transmitted, a greedy model using Fractional Knapsack is designed for 5G networks.

In recent years, IoT-based sensor nodes have attracted considerable attention, making them important for the smooth management of high data rate real-time applications. It is inevitable to learn and adapt to channel spectral features in order to guarantee the significant data transmission in IoT networks, in order to increase the rate of transmission and to share channel when necessary.

An automated and adaptive model was developed that led to a higher rate of information transmission and throughput based on the dynamic changes in the features involved in the channel in the IoT network. The method also required each node to define the attributes of the channels of the surrounding nodes so that maximum data transmission could be contributed.

After that, the best channel was selected based on the spectral characteristics and Gaussian radial function assigned unused spectrum to the next channels. This improved the efficiency, fairness and accuracy of classification. The time limit for access to spectrum was not concentrated, however. In this work, the improvement of channel throughput using Fractional Knapsack would concentrate spectrum access delays by applying for the Optimum Channel (spectrum) access Langrange, which not only minimises spectrum access delay but also optimises spectrum precision performance.

### 1.2 History :

Telecommunications evolution has been so swift in the last four decades that what we now take for granted were beyond even the most brilliant engineers' contemplation in the 1970s and 1980s. It all began when James Clark Maxwell discovered the electromagnetic waves in the 1860s, indicating they could be stronger than the sun. Heinrich Hertz found soon after a way to generate and track electromagnetic waves, which he later called the 'Radium Waves.' After such waves were discovered, luminous minds were thought to use it in informational carriers.

**1G:** The telecommunication system is often called the first generation and was first used by Americans and Europeans in their communication devices in the late 1940s and 1950s. Although these devices were advertised as mobile telephones, their size, safety problems and the obstacles to the transmission of signals were severely limited.

When NTT, Nippon Telegraph, and Telephone began the automated cell network, known as the First Generation Mobile Network, in 1979, the first time the proper cellphone was launched. 1G was a very primitive way to communicate wirelessly since the data was sent in the form of analogue signals. While there was a lot of noise in the communication, it was really a milestone in the field of telecommunications when a true "mobile" phone came to the customers.

**2G:** the second telecommunication technology generation. The signal transmission changed drastically. This generation used digital signal rather than analogue transmission as opposed to the previous generation. The world was first introduced in 1991 by Radiolinja when the paradigm change in cell technology was officially achieved. This technology solved the problems of the past century, i.e. that it transmitted the signals in digital form. , the information is digitally authenticated in order to receive and access only the intended recipient. The 2.5G and 2.75G were soon followed by a slightly polished iteration of the same technology. Even when the world came to see mobile internet networks, the GPRS and EDGE technologies with a potential bandwidth of 50 kilobits per sekunde and 1 megabit per second. A truly "mobile" mobile telephone and a bonus. Okay, what else would you ask for? Yet the planet needed more, it turns out. Even this "radical breakthrough" which could literally not fulfil bandwidth for email, was only made obsolete after a decade. and internet even when they were in their early stages.

**3G:** That was when 3G was released. The 3G technology was introduced by NTT in Japan at the start of the 2000s. 3G technology was first launched by NTT. Although the telephone calls and messages were little changed, one place where the data rates were 3G outside 2G. 2G technology data speeds were incredibly low. The data speeds were improved by 7.2 megabits per second with the introduction of a 3G system. It was also designed to make itself safer with protection from end to end. Following the 3G technology, 3.5G and 3.75G were added to the data rate limits. . This too was once thought to be revolutionary because it had a potential to provide its users access to the internet from any given location.

**4G:** In 2009, Oslo and Stockholm were the first launches of the fourth generation of telecommunications technology 4G, also known commercially as the LTE, offered considerably higher data rates of over 100 megabit per second with a capped load and a capped load of more than 50 megabit per second. Apart from improved protection and encryption, the other major changes in the 4G technology are latency. 4G technology has a response time of 50 ms which is way beyond enough at release for any conceivable mission. As described before, however, it turns out that there is still a mile of journey ahead of us when we believe we are nearly there. Isn't it amusing to think that any time a big technological advance happens, this is far more than the mark of innovation, but there is much more to be done? The way we believe telecommunications now is slowly evolving only because of the developments we have seen in the last four decades.

**5G:** 5G technology represents the 5th mobile technology generation (MT). 5G has been developed as a key technology to allow a broad range of sustainable development objectives, from safe to efficient energy usage and access to a sustainable environment. Nowadays, there are many kinds of contact, such as human to machine (H2M), machine to machine (M2M), and pair to pair computing (P2P). 5G networks enable people to connect to machinery, objects, and devices of IoT (the Internet of Things). The powerful combination of 5G, artificial intelligence, smart networks and IoT will transform the environment and deliver smart, sustainable connectivity in various applications and services. , Technology and platforms. The 5G network architecture aims to develop innovative services for the entering of telecom networks, along with new business strategies. The IoT has a range of applications in various areas, such as intelligent treatment, intelligent transport, intelligent agriculture and industrial automation, using computer communication. Thus, 5G network connectivity provides the opportunity to improve these technologies and allows new applications – such as car transport and agriculture – to be mastered. These applications nevertheless produce enormous quantities of cloud data. In accordance with a Gartner analysis, an end-to-end sustainable 5G infrastructure will be converted by 2025 to 2030 and deployed in most IoT and Artificial Intelligence (AI) applications.

### 1.3 5G Network Architecture

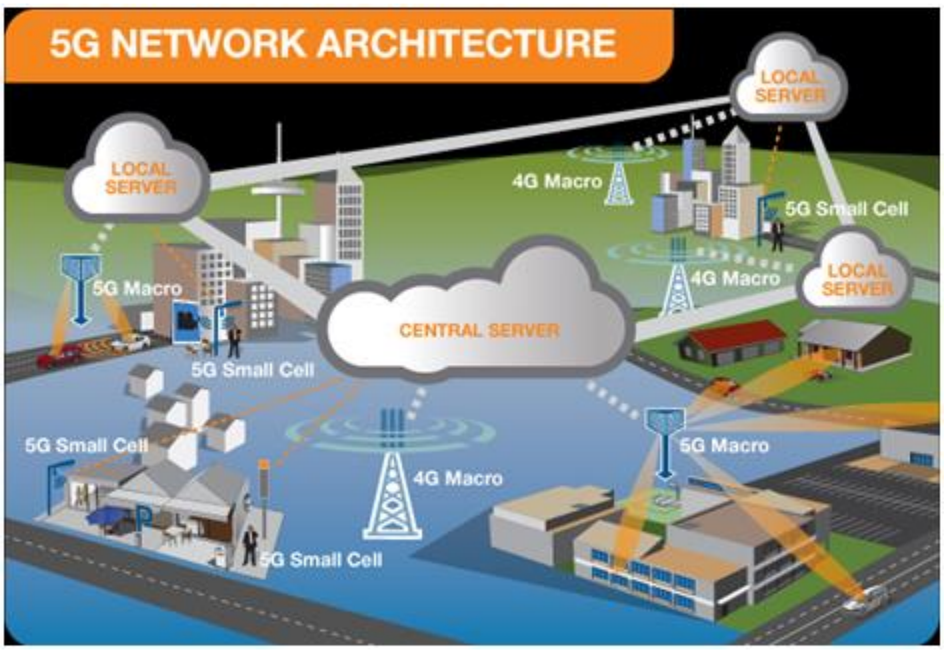


Figure 1. 5G Network architecture

In order to provide a continuous link, most operators would initially embed 5G networks in existing 4G networks.

Network 5G architecture with a 5G and 4G collaborative system, delivering quicker user content and low latency applications with central and local servers.

The 'Radio Access Network' and the 'Heart Network' represent two key components for a mobile network.

**The Radio Access network** – comprises a range of facilities, including small cells, towers, masts, building systems and home systems that connect mobile users and wireless devices to the principal core network.

The new millimetre-wave (mm Wave) frequencies at which a communication range is very low would require small cells as a major feature of a 5G network. Small cells are distributed in clusters to provide continuous connectivity depending on the need for a link to supplement a large-scale macro network.

5G Macro cells use the MIMO antennas, which have many elements or connections for sending (multi-input, multiple output)

And simultaneously obtain more data. Users benefit from being able to link more people to the network and retain high performance simultaneously. Where MIMO antennas use very many antennas, the physical scale is identical to the current 3 G and 4G base station antennas but are often referred to in 'huge MIMO.'

**The Core Network**: It is a telephone network of exchanges and data that handles both mobile, data and networks. For 5G the 'core network' is being restructured to fit better with web and cloud services and includes network-wide distributed servers that increase response times (reducing latency).

Many of 5G's advanced technologies, including virtualization of network operation and network slicing, are handled for various applications and services. A picture of local servers which provide users with faster content (film streaming) and low latency applications for car crash prevention systems can be found below.

**2.REVIEW OF LITERATURE:**

**Merima Kulin et.al. 2018[1]:** End-to-end learning is currently automatically taught using simple wireless signal images. No manual expert features were needed where certain spectrum models required cyclical patterns based on higher order factors. The trained method also removes the need for a complicated machine learning system for the wireless signal classification. In this context there was a conceptual framework for end-to-end learning with the implementation of wireless signal classifiers, including Spectrum monitoring and Accessing.

**Taimur Hassan et.al.2018[2]:** An automated and adaptive model was developed that led to a higher rate of information transmission and throughput based on the dynamic changes in the features involved in the channel in the IoT network. The method also required each node to define the attributes of the channels of the surrounding nodes so that maximum data transmission could be contributed.

**Ar Zheng Li et.al.2020[3]:** There was no emphasis on the interference intensity, imposing a big technological spectrum awarding challenge. A Deep Reinforcement Learning model has been developed to solve this issue, not only leading to optimum systems performance but also rapidly converging. Deep strengthening learning model serves to reduce the possibility of cellular interference and to increase the sum rate of D2D interfaces. However, the resource blocks were not automatically selected (RB).

**Kai Lin et.al. 2019[4]:** The spectrum use is important because of a spectrum shortage. In order to increase spectrum efficiency, AI techniques were implemented. Spectrum deficiency problems were not, however, fixed.

**Chaoqiong Fanet.al. 2018[5]:** Work on minimising the underuse of spectrum resources using the Nash Equilibrium Strategy (SNE) was developed to optimise the overall and latency levels. However, partial data was not taken into account.

**Jingjing Wang et.al.2019[6]:** In recent years NOMA has been widely praised and has become an important technology for 5G networks. It has a range of advantages over the current multiple access model, which allows multiple users to exploit dissimilarities in channel gains from different IoT devices on a similar resource block. With the NOMA and Fractional Knapsack models the proposed model ensures the optimum data rate and energy usage specifications for each IoT unit.

**Hamid Eltom et.al. 2018[7]:** No decrease in spectrum delay. This has led to the presentation of an additional spectrum dynamic spectrum model using a classification of statistical predictions frame. Information on the primary user's signal is designed to establish and dynamic spectrum access. Some of the few computer costs and the cumbersome procedure involved in determining threshold detection etc. are constraints faced by secondary users.

**Hassaan Bin Ahmad et.al.2019[8]:** To overcome these limitations and thus increase robustness, a new detection model was presented using machine learning.

**M. Weiner et.al.2014[9]:** A large proportion of the complexity of this ultra-dense network is leading to the fast expanding number of machine type communication (MTC). In order to achieve high availability, reliability and protection, very short transit times and low latency, many of the future 5G and beyond MCT applications would require the underlying wireless networks.

**Mekki et.al.2019 [10]:** IoT has the primary benefit of being able to communicate between an endless number of devices that are interconnected in a large wireless system. These automatic devices and sensors together generate and communicate data in real time that is useless when filtering and data are inaccurate or inadequate.

**D. Niyato, M. et.al.2017**[11]: The trend 5G allows IoT to include higher data rates and higher coverage, which provides options for business models and facilitates the use of robots, actuators and drones in IoT.

**S. Li et.al.2018[12]:** Innovation in the wireless industry, technology of the next generation and 5G growth allow IoT to provide state-of-the-art solutions, along with the need for broadband spectrum to meet rapidly rising traffic demands. Therefore, the 5G case management is desired to successfully allow IoT as proposed by 5G Americas, a combination of low band, mids and highband spectrum.

**Hongmin Gao et.al. 2018[13]:** To enhance classification accuracy, a CNN model was suggested. However, the delay in transmission was not reduced. For the channel detection and allocation a deep Q-learning model was examined. However, the precision of classification has not been improved.

**Y. LeCun et.al. 2015[14]:** In the 30s, AI methods were influenced by Turing machine theory, reinvigorated again through the development of deep neural networks in a broad range of research fields, including natural language processing, computer vision and wireless communications.

**Kim et.al.2013[15]:** 5G networks would have a control and information plane software-defined networking (SDN) architecture. Many aircraft control systems are instructed to handle the infrastructure by a data plane.

**3. 1 Full Spectrum Sharing Toward 5G**

CR technology allows valuable spectrum resources to be reused without modifying the current policy on the allocation of spectrums, thus solving the low utilisation rate issue. CR's key concept is to achieve spectrum sharing by using the complex spectrum and spectrum sharing ensures that SUs can use the idle spectrum of PUs, but only when they cannot interfere with contact with PUs. As shown in Figure 2, spectrum sharing typically consists of four steps.

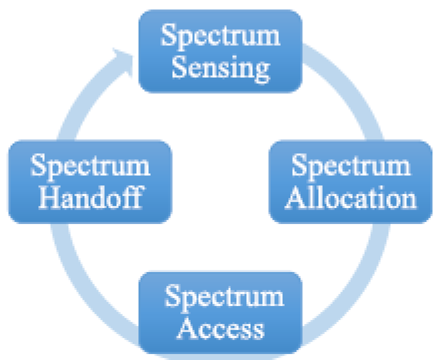


Figure 3.1. The spectrum sharing process.

1) **Spectrum sensing:** Spectrum sensing is the first step in the spectrum sharing that is necessary for ensuring interference, full spectrum sharing, enhancement of spectrum use and various CR applications for PUs. In multi-dimensional space, SU continuously recognises the PUs' frequency bands (such as time domain, spatial domain, frequency domain, etc.). Spectrum sensing is used to detect whether a PU is apparent and whether the spectrum hole is open. The exact perception of spectrum hole is thus the first step in the distribution of spectrums.
2) **Spectrum allocation** : The distribution of the spectrum is based on the spectrum holes available and distributes the spectrum to SUs. Since the spectrum holes are not set, SUs must compete with them, while the SU's quality level is different. The spectrum holes must therefore be used in a reasonable and effective manner. Spectrum allocation is crucial to developing efficient algorithms and rules on spectrum allocation that can increase the efficiency of spectrum usage in conflict minimisation or conflict-free conditions, ideally near the optimum goal.

3) **Spectrum access** : PU has priority frequency band access, while it is accessed by the SU as a subordinate connection. Spectrum access therefore requires a spectrum access algorithm for managing access to the spectrum of multiple SUs, thus preventing disputes between PUs and SUs.
4) **spectrum handoff:** when one of the following three conditions arises, SU must switch to the appropriate spectrum. The SU must exit this frequencyband and then turn to other spectrum holes, for the contact, when the SU uses the current spectrum hole, the appearance of PU will cause a collision between them. Second, if the geographical position of the SUs changes without changing the PU's geographical location, the spectrum holes for the SUs are different and must be switched to the correct frequency band.
Finally, if the frequency bands used by SUs cannot comply, they need to migrate to another frequency band that can satisfy their communications requirements.

### 3.2 Spectrum Management and Cognitive Radio

In the last decade, wireless networks and information traffic have risen exponentially leading to excessive demand for radio spectrum services. The radio spectrum is a finite resource that is regulatory regulated and controlled by recognised authorities like the FCC in the US. The new radio spectrum allocation scheme includes awarding licences for particular wireless technology and facilities to individual users. Those licenced users have access, even if those portions of the spectrum are unsettled, to that spectrum for transmission/receive their data. while some, even though certain parts of spectrum are unoccupied, are banned. Recent studies have shown that the use of the spectrum in the US varies between 15 and 85% under FSS regulation. FCC measurements also suggest that some channels are used extensively while others are used sparsely as shown in Figure 2.

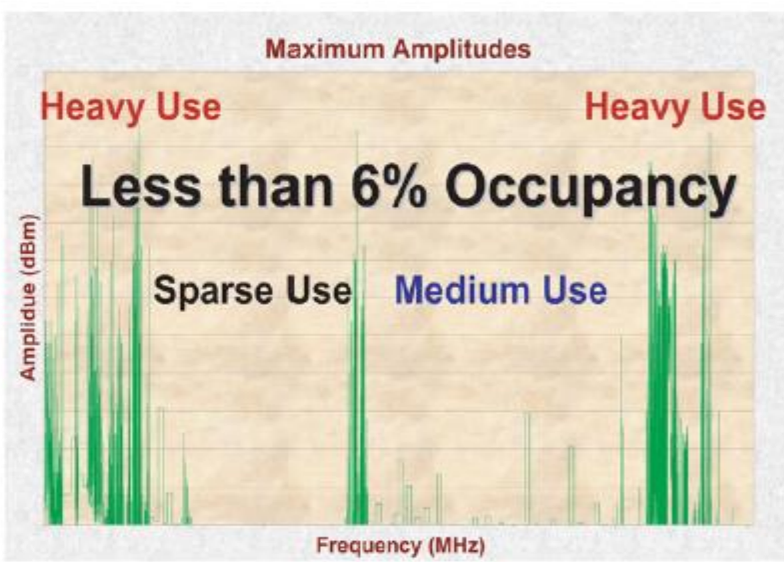


Figure 3.2: Radio spectrum occupancy

The allocated spectrum portions, called primary users (PUs), which generating spectrum holes are not constantly used by their owners. A spectrum void, also known as a white gap, is a PU's frequency band, but is not used in a specific time and position. The radio spectrum has thus been used inefficiently[8][9]. Therefore, spectrum management's shortage and inefficiency demand immediate action to expand access to radio spectrum and to hit high network performance. A safer way of solving the spectrum shortage problem is by sharing unoccupied channels with noncompatible devices who are referred to as secondary users (SUs), PUs signals without interruption. The proposal to fix spectrum allocation issues was made to provide opportunistic access to spectrum (OSA), also called dynamic spectrum access (DSA). Unlike the FSA, DSA allows the spectrum to be split into multiple bandwidths for one or more dedicated users among licenced and non-licensed users. A variety of solutions, including cognitive radio, have been suggested to facilitate the use of the OSSA. Mitola says cognitive radio is a smart transmitter/receiver for radio frequency, designed to detect the available channels and change their transfer parameters to allow further communication. and enhancing the efficiency of radio operations. A cognitive radio system can observe and learn from the environment, adapt to the environment, and make decisions to use the radio spectrum more effectively. This allows SUs to use the radio spectrum allocated to PU when it is not used as seen in Figure 3.

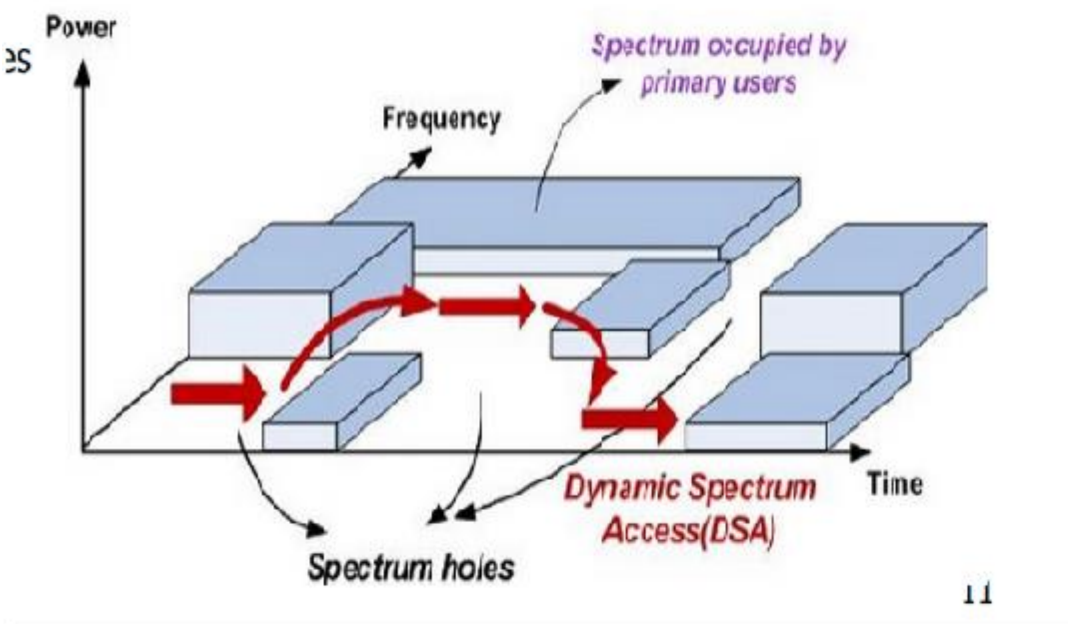


Figure 3.3: Dynamic spectrum access

Cognitive radio is considered to be the future technology to address the issue of resource allocation posed by the 5th generation Wi-Fi. With this 5th generation of wireless communications, the big wireless network provides high service quality and data speeds. The IEEE 802.22 standard was described as the first cognitive radio solution achievement to allow SUs to use the VHF and UHF TV white spaces.

### 3.3 Network model and assumptions

Models for the network and spectrum sensing performed via a cluster head (CH) at each gateway will be shown.

A 5G heterogeneous IoT network is presented for spectrum and access. The design has many primary networks that are usable for many platforms. Each primary network comprises several clusters with "IoT devices and" channels in each cluster. Each primary network consists of several clusters. In this work, we look at two-fold architecture according to the characteristics of the IoT, as shown in figure 1. Due to the conditions of the object in IoT and the association of various types of IoT equipment The nodes in these devices must be arranged accordingly. In this case, in the botmost fold the nodes or IoT devices form various networks of mesh and the most advanced networks of star topology. Devices in a single-hop network communicate with the analogue CH in the lowest mesh, and cluster heads are connected.

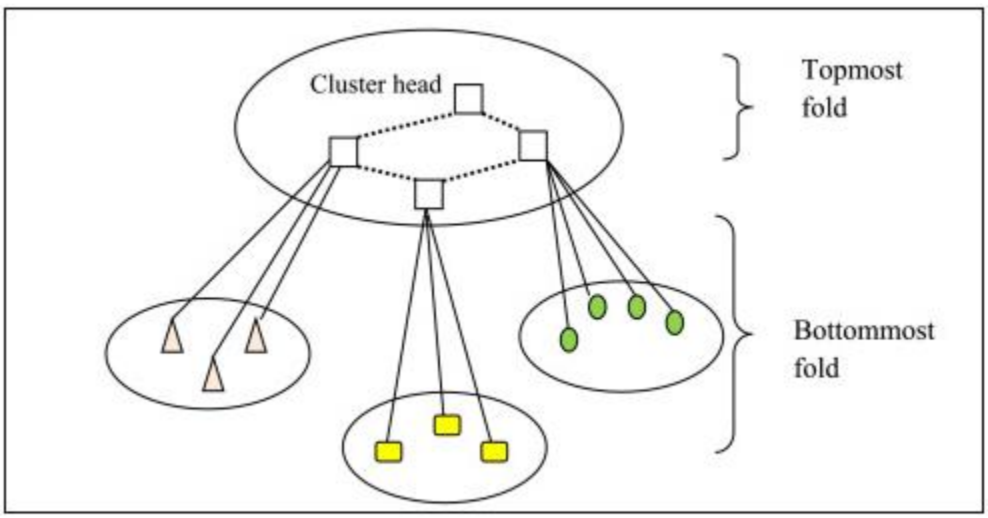


Figure 3.4 Sample two-folds architecture

## 4.Research Methodology

The structure proposed is discussed in this section. The key topic is divided into two phases of the proposed system. Phase 1 concerns the selection of the spectrum and phase 2 concerns the access of the free spectrum.

Energy detection is another approach to primary spectrum detection by the consumer. The low computational and implementing complexity of this approach is known to be the most common way to detect signals. In energy detection, the receivers need not have any knowledge of the primary consumer signals, unlike matched filters and other approaches. This method compares the output from the energy detector with a certain threshold value, the threshold value depending on the noise level and can be calculated based on that, as in waveform. The effect of this method is a signal detection. The digital implementation of energy detection is shown in Figures 4.1 (a) and (b). The first signal is transformed from analogue to digital in the periodogram method as in Figure 4.1(a). The Fast Fourier Transform is used (FFT). The FFT process output is squared and summed to obtain test statistical results. The absence or presence of the signal in the given band is defined on the basis of test statistics. The signal is prefiltered before converting analogue to digital in the analogue pre-filter method as shown in Figure 4.1(b). This is accompanied by the digital transfer of the signal.

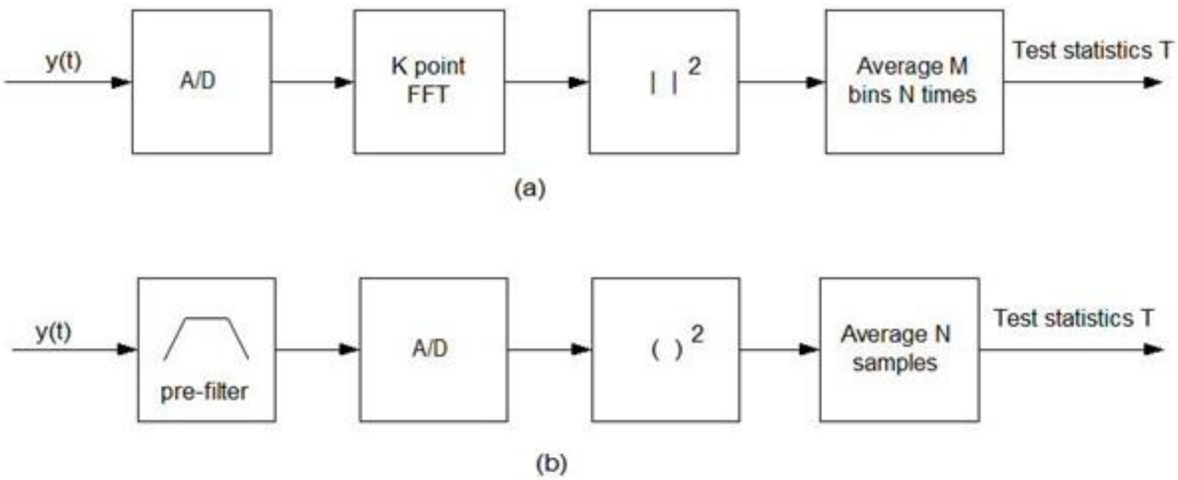


Figure 4.1. Digital implementation of energy detection (a) with periodogram: FFT magnitude squared and averages, (b) with analog pre-filter and square-law device

Test figures squaring and averaging. The statistics are compared in both implementations with the given limits and then decisions on the presence or absence of a signal are taken.

For energy detection, the device model in (3) can be considered and the decision metric can be calculated as

$$D = \sum_{n=1}^{N} | y(n) |^2$$

The decision metric D is accompanied by the 2N degree of freedom distribution (Ś2N)2 assuming the variance of AWGn μn and the variance of a signal μs, two hypotheses could be modelled accordingly;

$$D = \begin{cases} \dfrac{\sigma_w^2}{2} \chi_{2N}^2 & H_0 \\ \dfrac{\sigma_s^2 + \sigma_w^2}{2} \chi_{2N}^2 & H_1 \end{cases}$$

In this method you may measure the erroneous warning probability PF and true detection probability PT using two hypotheses that compare the threshold value selected as in (9). We note again that the method has some drawbacks such as the undesired likelihood of true detection and false warning, poor performance at low Signal-to-Noise ratio (SNR), and the inability to distinguish between interference from licenced users and noise which may restrict the performance of this approach if threshold value is not chosen properly. In addition, this method does not detect such CDMA signals optimally.

### 4.2 Fractional Knapsack and Langrange Hyperplane Spectrum Access framework

IoT devices produce huge data. The rapid production of IoT is limited to a limited range of radio. This is because of the various spectrums of networks involved in IoT. However, the range is not very scarce in frequency, but it is said that it is under-utilized and that the radio environment knowledge is actually chosen effectively. This work aims to enhance both the accuracy of spectrum access and the throughput with minimum spectral access delay by means of an FK-LHSA architecture for IoT sensor network. The block diagram of the FK-LHSA sense is shown in Figure 2 below.

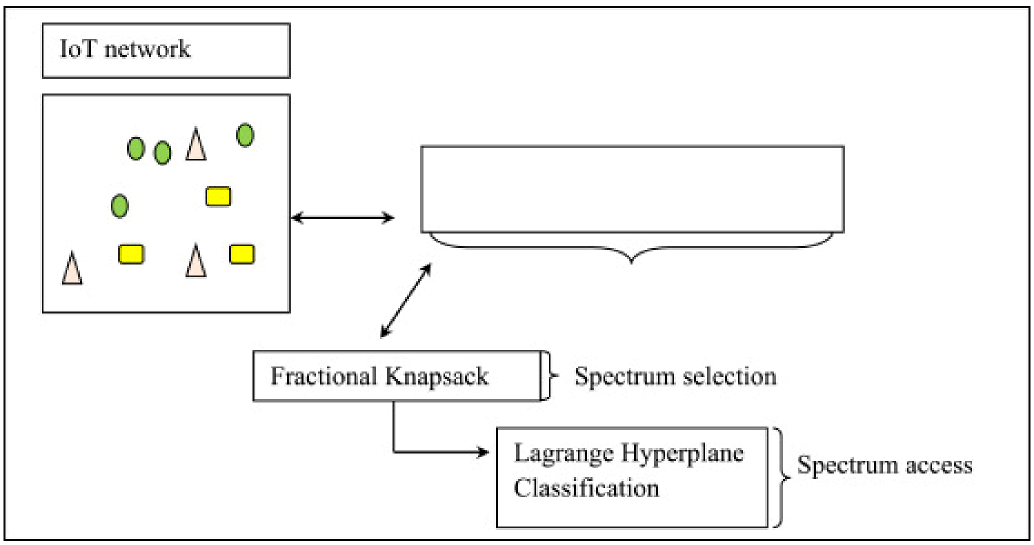


Figure 4. 2 Block diagram of FK-LHSA framework

The system is divided into two stages as shown in the above FK-LHSA framework. The EPSDLAC technology initially takes the IoT network input. The preprocessing is done for extracting undesirable data and selecting the data concerned. Preprocessing reduces complexity and dimensionality of time. The first step uses the Fractional Cnapsack model to pick a spectrum. In the second level, the Lagrange Hyperplane Classification refers to spectrum access. The following parts provide a comprehensive overview of the above structure.

### 4.3 Fractional Knapsack Multiband Spectrum Selection

NOMA has become a widely respected technology in recent years and has been a core technology for 5G networks. NOMA has gained significant attention. Compared to existing multi-access models, it has many advantages that support multiple users in a resource block, but that use the channel benefit differences of various IoT devices. By using NOMA and the Fractional Knapsak power consumption models, the proposed model ensures optimal data rate requirements and optimum energy consumption for each IoT unit. Each IoT device determines whether or not a multi-band spectrum selection process participates based on the availability of its residual energy. The CH then assigns those spectra to IoT devices which have enough energy to select a multi-band spectrum, while lower powered IoT devices do nothing before a location is selected. The CH then integrates the effects of spectrum selection from IoT instruments and conducts a variety of tests to decide whether or not primary users exist on each spectrum.

We use an FKMSS model in this work. If the IoT system has enough energy and data to transmit, a certain number of objects, i.e. IoT devices and channels, indicates its minimum data rate specification for the CH during spectrum selection. Now that CH is responsible for managing all "channels," the programming of spectrum to IoT devices is said to be efficiently carried out according to the specifications of the requested IoT devices. This Fractional Knapsack specifies that the total number of items to incorporate in a set is less than or equal to a given threshold and the total value is as large as possible. (i.e. either chosen for an IoT system with a given channel or not)

In this work, with several IoT devices considered, each set of IoT device are broken into smaller pieces (i.e. fraction) and hence called as the FKMSSmodel.

### 4.4 Langrange Hyperplane Optimum Spectrum Access

Latest advances in computing and AI have intrigued academics and researchers alike to advantage AI explicitly within the 5G background in the area of wireless communications. The cluster heads have the capacity to build an entire data repository by separating, processing, and interpreting optimum spectrum allotments across an AI-defined 5G network. However, during system contact, when spectrum is not correctly assigned, significant interference is said to occur. A x model is used for equal and efficient spectrum allocation to mitigate this interference. In this work, we adopt a Support Vector Machine to train a classifier that solves the optimization problem by maximizing the margin while minimizing the sum of errors.

## 5. Results and Discussion

We will examine the proposed system in this section in terms of the number of IoT units, spectrum access delays and spectrum accuracy.

**Throughput**

The output is defined as the ratio of the channel assigned to the available (in terms of Mbps)

Canal (in terms of Mbps). The following is conveyed.

$$Th = \frac{cH_{alloc}}{cH_{avail}}$$

The overput ratio 'Th' from the above equation is determined by the channel allocated cH allocand the availability of the channel cH avail mega bits per second (Mbps). Table 2 below shows the efficiency of the FK-LHSA and two

Methods already in operation.

**Table 2 Comparison of throughput**

| Number of IoT devices | Throughput (Mbps) | | |
|---|---|---|---|
| | **Proposed FK-LHSA** | **Existing End-to-end learning** | **Existing Fully automated model** |
| **15** | 66 | 55 | 44 |
| **30** | 60 | 50 | 40 |
| **45** | 58 | 45 | 40 |
| **60** | 55 | 50 | 35 |
| **75** | 50 | 45 | 32 |
| **90** | 45 | 40 | 30 |
| **105** | 40 | 35 | 25 |
| **120** | 42 | 30 | 20 |
| **135** | 40 | 28 | 23 |
| **150** | 38 | 31 | 25 |

Table 2 displays the megabit per second (Mbps) throughput measurement in relation to different IoT system numbers in the range 15 to 150 distinguished by the serial sensor number.

**Spectrum access delay**

The time delay in spectrum access refers to the time delay when the corresponding IoT units are assigned to spectrum. The lower the spectrum access time, the higher the amount of IoT system replies. This is expressed as shown below mathematically.

$$SA_D = \sum_{i=1}^{n} D_i [SAReq_t - SARes_t]$$

From the above equation , the spectrum access delay $'SA_D'$ is measured based on the spectrum access request time $SAReq_t$ and the spectrum access response time $SARes_t$ with respect to the different numbers of IoT devices '$D_i$' It is measured in terms of milliseconds (ms).

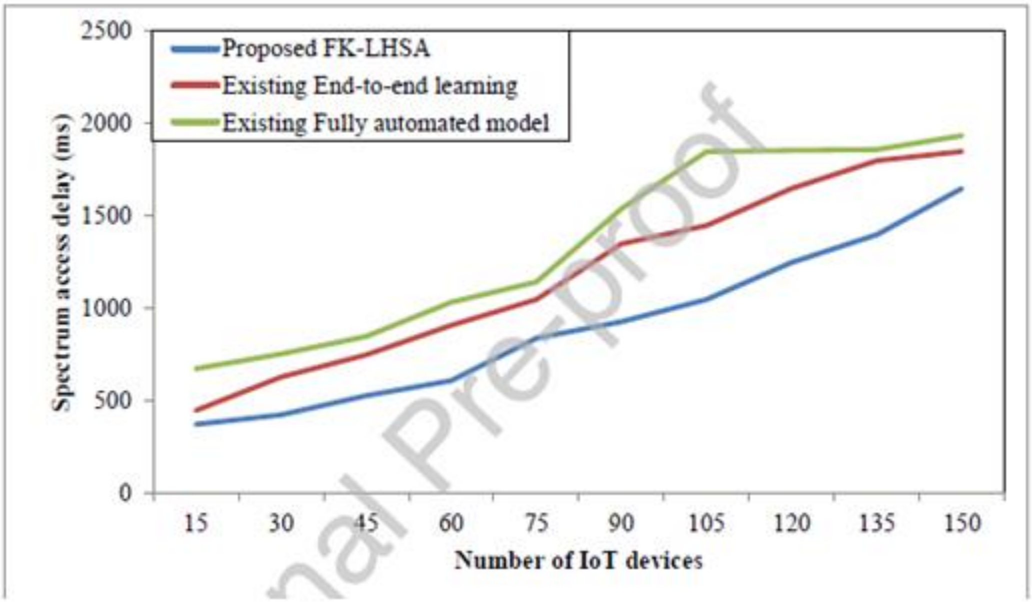


Figure 5.1 Spectrum access delay against the number of IoT devices

The spectrum access delay for 150 separate IoT system numbers is shown in Figure 6 above. The latency of access in spectrum is seen for three different approaches. The figure shows that the spectrum access latency is also increased in all three methods by increasing the cloud of IoT devices. This is because the time to assign the spectrum only depends on the vacant spectrum with the higher number of IoT devices on the queue for the spectrum submission. This raises the latency of access to the spectrum. The spectrum access delay was found to be '375ms' from the simulation of '15" IoT units. Using FK- LHSA, [1] '450ms' and [2] '675ms.' As a result, the delay to reach the spectrum by the FK-LHSA in relation to [1] and [2] has been observed. This is because the utilities function for any IoT system determines the spectrum band at first and according to the parameters of the service form. The transmission capacity is then also calculated on various sub canals of the spectrum. This reduces FK-LHSA by 25% in relation to [1] and 35% in comparison to [2]. In the case of FK-LHSA, spectrum access delays or spectrum allocation time are decreased by 25%.

**Spectrum access accuracy**

The spectrum access accuracy '$SA_{acc}$' refers to the percentage ratio of the available channel '$c_{Alloc}$' to the allocated channel '$c_{Avail}$'. It is measured in terms of percentage (%). The spectrum access accuracy is measured as given below.

$$SA_{acc} = \frac{CAlloc}{CAvail} * 100$$

**Table 3 Comparison of spectrum access accuracy**

| Number of IoT devices | Spectrum access accuracy (%) | | |
|---|---|---|---|
| | Proposed FK-LHSA | Existing End-to-end learning | Existing Fully automated model |
| 15 | 96 | 90 | 84 |
| 30 | 92.15 | 87.55 | 82.15 |
| 45 | 90.35 | 86.55 | 80.35 |
| 60 | 88.15 | 85.35 | 80.15 |
| 75 | 88.75 | 84.25 | 80.11 |
| 90 | 90.35 | 84.55 | 80 |
| 105 | 92.45 | 82 | 80 |
| 120 | 90.15 | 80.35 | 80.25 |
| 135 | 88.35 | 80.25 | 80 |
| 150 | 86.45 | 80.15 | 80 |

The spectrum access precision for 150 different IoT devices performed in 10 runs for simulation is shown above in Table 3. In this case, the accuracy of spectrum access is calculated based on the channel available. Due to its lower limit and upper limit, and due to the aggregate frequency resolution, the assigned channel or frequency varies for different IoT devices. However, the accuracy of FK-LHSA 90 percent with [1] and '84' with [2] was demonstrated with simulations for '15' IoT units. Application of the LH spectrum access algorithm induces a percentage increase in FK-LHSA.

By applying this algorithm, the optimal allocation of the spectrum is arrived at using Lagrange function. This in turn improves the spectrum access accuracy using FK-LHSA by 7% compared to [1] and 12% compared to [2] respectively.

**6.Conclusion and Future Scope**

In this paper, we introduced a greedy IoT system that allows the selection of the spectrum and access to the spectrum. First, the licenced band senses free spectral channels and assigns them to the respective IoT units. The decision is taken by a CH concerning the assignment of these networks. First, spectrum selection is rendered with the implementation of energy consumption models NOMA and Fractional Knapsack. This is accompanied by the application of LH to the spectrum. This decreases the latency of spectrum access and increases the precision of spectrum access and channel throughput. The results for the various parameters according to the different models indicate the validity of the system proposed. Therefore, potential analysis can be carried out with various methods of master learning to analyse the time complexity. To improve spectrum efficiency, the algorithm AI-driven data-analytic-based spectral allocation (ADASA) is used.

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