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HANDOFF IN WIRELESS NETWORKS BASED ON QOS METRICS: A SURVEY AND TAXONOMY

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ABSTRACT

Wireless communication is undergoing a paradigm shift with emergence of high, performance machine learning (ML) computing and internet of things (IoT). The demand for bandwidth has significantly risen due to multimedia applications and high, speed data transfer. However, with increasing number of cellular users, the challenge is to effectively manage the limited spectrum allotment for wireless communication while maintaining satisfactory quality of service. Hence, different multiplexing techniques have been used to effectively use the available bandwidth. Recently, the concept of automatic fallback in receivers are gaining popularity due to high mobility in vehicular networks and IoT. Automatic fallback and handover mechanisms often utilize the channel state information (CSI) of the radio and can switch between technologies to provide the best available quality of service for particular spatial and temporal channel conditions. With the advent of machine learning and deep learning methods, estimating the channel state information has become computationally efficient and feasible thereby improving the performance metrics of the system. This paper presents a comprehensive review on the need for cognitive systems with CSI availability, handover mechanisms in wireless networks and different strategies involved in estimating the channel state information for wireless networks.

Keywords: Wireless Networks, Handover, Channel State Information (CSI), Cognitive Networks, Machine Learning (ML).

1. INTRODUCTION

Wireless communications beyond 5G has emerged as new paradigm with enormous new possibilities such as metaverse, digital clones, large scale automation and internet of things to name a few [1]. However, all these new age concepts critically depend on the bandwidth availability and spectrum management in wireless networks. As bandwidth is limited, hence, effectively using the bandwidth is critically important to cater to the following needs [2]:

1) Increasing number of users.
2) Increased bandwidth requirement owing to multimedia data transfer.
3) Need for high data rates.
4) Limited available bandwidth.

The problem becomes even more critical with the necessity of internet of things (IoT) and fog computing networks where multiple devices are connected over internet and send data to a centralized server [3]. The IoT framework is depicted in figure 1.

There are several applications of IoT such as:

1) Manufacturing and automation.
2) Climate monitoring.
3) Communications and robotics.
4) Defense
5) Medical applications etc.

Fig.1 The IoT framework

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The IoT framework has its own set of limitations in the sense that that is a lot of device cluttering in the near 2.4GHz Industrial scientific and medical (ISM) band. IoT based networks can be further classified as [4]:

1) Cellular based IoT
2) Device to Device based IoT.

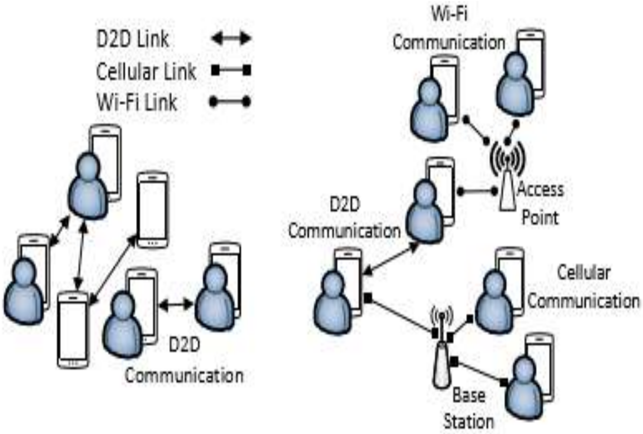

Figure 2 depicts the D2D and Cellular based IoT models.

Another variant of the IoT framework is the fog computing architecture for last mile connectivity. Fog infrastructure supports heterogeneous devices, such as end devices, edge devices, access points, and switches. Fog servers are considered to be micro data centres by inheriting cloud services at the network edges [5]. The fog computing architecture is depicted in figure 3.

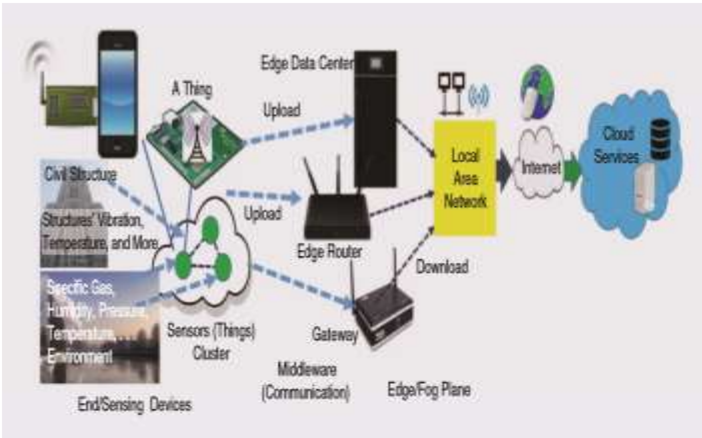

Fig.3 The fog architecture

2. NEED FOR FALLBACK AND HANDOVER.

The need for fallback and handover stems from the fact that different modulation

techniques perform differently for different channel environments [6]. While frequencies can be re-used over distances, yet the conditions for frequency reuse factor needs to be considered. Figure 4 depicts the scenario for frequency re-use.

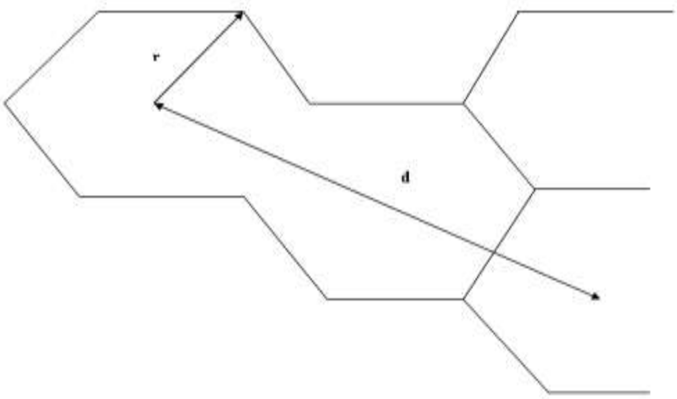

Fig.4 Re-Using Frequencies in geographically distant regions.

The frequency ‘f’ can be reused at a cell site ‘d’ km away for a cell with radius ‘r’ keeping in mind the reuse factor:

$$q = \frac{d}{r} \quad (1)$$

Here,

q is the re-use factor.

r is the cell radius.

d is the distance of re-use.

Typically, in wide area networks and metropolitan area networks, if multiple IoT clusters are connected to a single Cloud Server in a cell, then such a cell is called a Macro Cell [8].Macro cells may have a large number of IoT devices (IoTDs) connected. The scenario of such IoT clusters is depicted in figure 5.

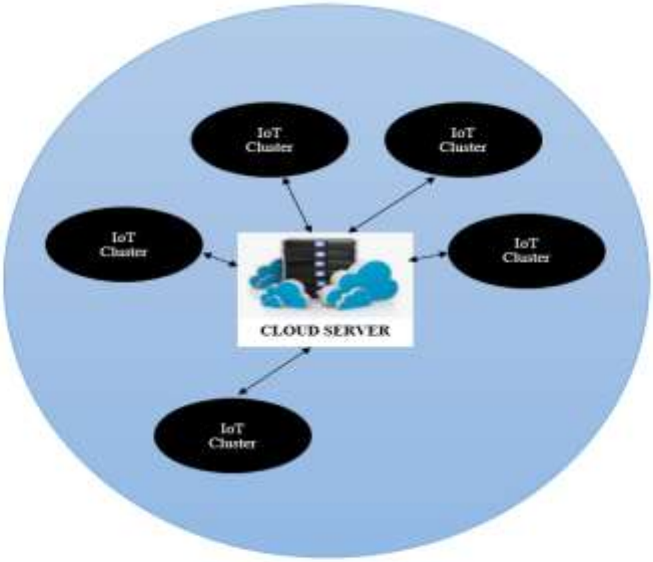

Fig.5 IoT clusters connected over cloud.

The major constrains of IoT and fogm, based networks are [9]:

1) Devices are resource constrained.
2) Number of devices are exceedingly large.
3) Networks can be used for extremely time critical applications with latency causing seriousrepercussions.

Thus, selecting an appropriate multiplexing technique is necessary to address the following issues [10]:

1) Lesser Bit Errors.
2) Low or acceptable limits of outage.
3) Acceptable latencies.
4) Effective spectrum management.

The major multiplexing techniques which are employed are [11]:

1) FDM
2) TDM
3) OFDM
4) NOMA

In FDM: Different users have different frequencies.In TDM: Different users have different times slots.In OFDM: Different users have different orthogonal frequencies.In NOMA: Different uses have different power levels. In NOMA, different uses may have SAME time slot and frequency, but the power level should be different. Figure 6 depicts the spectrum of FDM, OFDM and NOMA.

Table 1. Comparison of OFDM and NOMA

OFDM	NOMA	Reference
Signals separated in Frequency Domain	Signals Separated in Power Domain	Cai et al., "Modulation and Multiple Access for 5G Networks, IEEE 2017 [12].
Condition of Orthogonality Necessary	No need of orthogonality	Cai et al., "Modulation and Multiple Access for 5G Networks, IEEE 2017.

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Lower Throughput (Mbps)	Higher Throughput (Mbps)	Nain et al., User Selection with optimal power allocation in Downlink NOMA, IEEE 2017 [13]
Lower Sum Rate (Bits/s/Hz) (Spectral efficiency 'ɳ')	Higher Sum Rate (Bits/s/Hz) (Spectral efficiency 'ɳ')	D Tse & P Viswanath, Fundamentals of Wireless Communication, 2004 (Book) [14].
Receiver Design less complex	Receiver design based on interference cancellation much more complex	Guerreiro et al., "On the Receiver Design for Nonlinear NOMA-OFDM Systems, IEEE 2020 [15]
OFDM is less susceptible to path loss and multipath fading compared to NOMA	NOMA is highly susceptible to path loss in case of fading channels and may result in poor quality of service	A Al Khansa et al., Performance analysis of Power-Domain NOMA and NOMA-2000 on AWGN and Rayleigh fading channels, Journal of Physical Communication, Elsevier 2020 [16].

OFDM and NOMA often exhibit similar SNR-BER characteristics. A typical cellular system generally has the capability of adaptive fallback or automatic fallback [17]. In such cases, there can be a switching from one of the technologies to another parallel or co-existing technology in case of changes in system parameters such as Bit Error Rate (BER) etc.NOMA and OFDM can be shown to co-exist in case they can share similar bandwidth parameters and have a comparative BER performance over the SNR range chosen so that automatic fallback or handover is not a problem. Thus two major fallback or handover mechanisms are commonplace which are:

1) OFDM-NOMA
2) Cellular-Device to Device-Wifi

3. MULTIPATH PROPAGATION AND SYSTEM OUTAGE

The main objective of handover is to maintain a satisfactory quality of service metric.The outage of the system is measure of the quality of service of the systems. The outage means the chance of unacceptable quality of service. The outage primarily depends on the signal to noise ratio and the bit error rate of the system. The system outage often is represented in terms of the complementary cumulative distribution function or the CCDF. The need for using a probabilistic model for the description of the outage of the system is due to the fact that neither the BER no the SNR of the system can be used to ascertain the outage since both are subjective performance metrics [18]. In general, it is shown that the outage is a function of the signal to noise plus interference ratio, the distance and the channel fading effects. The outage in terms of absolute parameters $q(\lambda)$ is given by [23]:

$$q(\lambda) = \exp\left\{-\frac{2\pi^2}{\sin\left(\frac{2\pi}{\eta}\right)} R_k^2 SINR_k^{2/\eta} \lambda\right\} \quad (2)$$

Here,

$K_k = C_k R_k^2 SNR_k^{2/\eta}$ is a constant depending on system and channel parameters

SINR represents the signal to noise plus interference ratio

R is the distance

λ_j is the device density in a network

σ_{kj} is the shadowing factor

$q(\lambda)$ is the absolute outage

Mathematically, the CCDF analysis of outage is given by [24]:

$$ccdf(x) = 1 - cdf(x) \quad (3)$$

Here,

ccdf denotes the complementary cumulative density function of the D2D Networks system

cdf denotes the cumulative density function of the network.

x denotes a random variable.

4. MACHINE LEARNING ASSISTED HANDOVER

The enhancements in chip fabrication and computational power have made it possible to analyze copious amount of data at real time and on miniaturized systems on chip (SoCs) [19]. Machine learning (ML) models can be have the capability of analyzing large and complex data sets practically infeasible with conventional statistical models [20]. Machine learning models can be classified as [21]:

1) Unsupervised Learning: In this approach, the data set is not labelled or categorized prior to training a model. This typically is the most crude form of training wherein the least amount of apriori information is available regarding the data sets [22].
2) Supervised Learning: In this approach, the data is labelled or categorized or clustered prior to the training process. This is typically possible in case the apriori information us available regarding the data set under consideration.
3) Semi-Supervised Learning: This approach is a combination of the above mentioned supervised and unsupervised approaches. The data is demarcated in two categories. In one category, some amount of the data is labelled or categorized. This is generally not the larger chunk of the data. In the other category, a larger chunk of data is unlabeled and hence the data is a mixture of both labelled and unlabeled data groups.

Often, another sub-categorization made is the reinforcement learning which the type of learning in which the aim is to adjust the training parameters so as to maximize the rewards in certain circumstances. They may also possess categorically classified targets prior to training. Typically, some paradigms separate out machine learning and deep learning. In case of deep learning, the number of hidden layers are multiple and no separate feature extraction is done, and the data is directly fed to the neural network [23].

Machin Leaning and Deep Learning based techniques can be used to estimate the channel state information through several training parameters such as:

1) Channel Gain
2) Fading effects
3) Shadowing parameters

Thus, the correlation among the independent variables and target variable can be estimated through the training process.

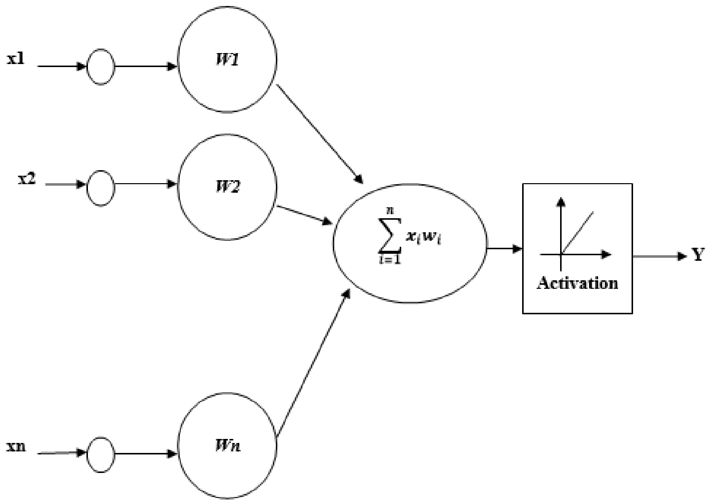

Fig.6 Neural Network Model

The neural network model is the most effective training model used for pattern recognition for deep learning models and is depicted in figure 14.

The mathematical relationship between the various parameters is given by:

$$y = f(\sum_{i=1}^{i=n} X_i W_i + \theta) \qquad (4)$$

Here,

X represents the inputs

Y represents the output

W represents the weights

Activation represents the behavior of the neural network while decision making

The model can be trained with time spaced input-target data corresponding to the channel to attain the updated CSI.

Moreover, by estimating the channel response, the design of equalizers can also be done [24]. The equalization mechanism can be used to mitigate the negative effects of noise and distortions in the channel. Such a mechanism is depicted in figure 1

5. CONCLUSION

This paper presents a comprehensive review on the currents trends in wireless networks pertaining to modulation techniques, handover mechanisms and automatic fallback, fading effective and channel sensing through latest machine learning and deep learning algorithms for cognitive networks. Moreover, internet of things (IoT), fog computing, device to device networks and their co-existence in underlay cellular networks have also been discussed. Channel sensing mechanisms through channel sensing and estimation of channel state information (CSI) for the design of equalization mechanisms have also been cited and discussed in detail. Moreover, the significant and noteworthy contributions in the domain have also been presented with the approach used, novelty of perspective and findings. The findings of the paper indicate that stochastic and big data analytics methods can be explored to design optimal handover and equalization methods for future generation wireless networks aiming high data rates, low error rate and outage to maintain satisfactory quality of service (QoS)

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