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Coexistence Management in Wireless Networks-A Survey

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ABSTRACT The rapid proliferation of wireless networks poses a great challenge of effective coexistence management amongst a plethora of wireless communication protocol users that are co-located and contending for the ever scarce spectrum available. For effective spectrum utilization and optimum performance of existing wireless networks and for the realization of new wireless networks, coexistence management of the wireless spectrum is the key to ensure the performance of multiple wireless networks in close proximity. This paper provides a comprehensive review of state-of-the-art coexistence protocols in wireless networks. The paper not only discusses wireless interference detection techniques in detail but also provides various coping mechanisms to counter the interference.

INDEX TERMS Coexistence management, wireless signal identification, cross technology interference, ISM bands, spectral analysis, interference aware routing, spectrum monitoring, deep learning, Q-learning, machine learning, interference management.

I. INTRODUCTION

Wireless networks like Wireless Personal Area Network (WPAN) mostly use the ISM (Industrial, Scientific and Medical) band for communication which is a collection of unlicensed frequency bands reserved globally for ISM applications. Due to high number of existing ISM users and with the upcoming next generation wireless technologies including Industrial Internet of Things (IIOT) and Cyber-physical systems (CPS), the spectral coexistence within ISM band is a growing concern in research community.

The resulting Cross Technology Interference (CTI) would result in packet drops and subsequent retransmissions which would cause latency and low spectral efficiency. Hence coexistence management schemes play a significant role in order to ensure the QoS of wireless networks in an already congested spectrum [1].

Wireless networks are highly dynamic with unknown and complex radio spectrum occupancy and varying spatial environments that change with respect to time with user mobility. They are affected by multiple factors such as multipath, fading effects, intentional jamming, unintentional interference caused by spurious RF signals from electrical machines etc. CTI interference is an addition to the existing challenges faced by wireless signals. The importance of existing commercial wireless applications in the ISM bands is undeniable as we are highly dependent on internet based services such as positioning (Google Maps), transport services (Uber), communication applications (WhatsApp, WeChat), delivery services (Postmates) etc. This is just a facet of the services that we consider essential in our daily lives from the many internet based applications available. With the growth in technology, connectivity at all levels has exponentially grown and so have the number of users.

Coexistence Management would be the key enabler of the innovative technologies being envisioned. Since unlicensed bands are the basis of many future wireless networks, it is imperative to coordinate the heterogeneous transmissions over space, time and frequency so that bare minimum communication is maintained instead of a complete network failure due to rising interference.

In the rest of the paper, Section II provides the introduction and technical specifications of several wireless communication technologies along with their interference foot prints. Section III discusses the various coexisting challenges of shared spectrum. Section IV gives a general introduction to Machine Learning (ML) techniques that are widely used in the works analyzed in the coming sections. The survey of the state of the art interference detection techniques are presented in Section V followed by the survey of solutions/schemes to tackle wireless coexistence problem is provided in Section VI. Section VII lists the future works

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and open challenges of this research area. The conclusion is discussed in Section VIII followed by references.

II. WIRELESS NETWORKS

In this section Wireless Networks using ISM band are discussed along with their technical specifications and bandwidth utilization. Moreover the applications which these networks are targeting and due to the dense nature of deployment, the interferences these networks cause with other wireless networks are analyzed.

A. IEEE 802.15.4 BASED LR-WPANS

Wireless Sensor Networks (WSNs) are based on the IEEE 802.15.4 standard comprising of low power sensing nodes that are spatially distributed. Sensing nodes gather data from the environment and synchronize the data to a central sink directly or via peer to peer data forwarding. WSNs are implemented in following scenarios.

- BANs (Body Area Networks) [2] for the collection of blood pressure, temperature, heart rate, respiration rate, oxygen saturation levels, pulmonary pressure levels etc. [3]–[7].
- Patient monitoring and rehabilitation [8].
- Home based WSNs for home automation and security [9], [10].
- Wild life [11] and habitat monitoring [12].
- Disaster monitoring in fires [13], tsunami [14], earthquakes [15]–[17] and landslides [18].
- Environment monitoring for air pollution, deforestation, weather, water quality [19], agriculture [20], [21].
- Industrial environment monitoring in sensor data aggregation [22] and machine health monitoring [23].
- Security applications such as area surveillance [24]–[26] and target tracking[27].
- Infrastructure monitoring such as in sewerage system monitoring systems [28].
- Ground, ship and air based logistics tracking [29].
- Space based WSNs [1] for e.g. Nanosatellite based WSNs, LEO (Leo Earth Orbit) based WSNs [30], indoor WSN in the ISS (International Space Station) [31].

WSN nodes often operate in harsh environments with limited power resources and on-board signal processing capability. Other derived standards include ZigBee, ISA100.11a, Wireless HART (Highway Addressable Remote Transducer Protocol), MiWi (Microchip Wireless), SNAP (Synapse Network Appliance Protocol), Thread, 6LoWPAN (IPv6 over Low-Power Wireless Personal Area Networks), RF4CE (Radio Frequency for Consumer Electronics).

Due to a variety of applications and usability of WSN, different coexistence scenarios with different technologies are possible. An empirical analysis of WSN coexisting with WiFi is studied in [32]. A more comprehensive study is done in [33] for coexisting WSN, WiFi and Bluetooth networks. Asymmetric interference is observed in the case of WiFi which corrupts the Frame Error Rate of WSN transmissions by 41%, whereas in the inverse experiment, WiFi remains unaffected by concurrent WSN transmissions. The effect of BL is less severe causing 10% FER (Frame Error Rate) to WSN transmissions.

B. WIFI

Wi-Fi (Wireless Fidelity) is a Wireless Local Area Network (WLAN) based on the IEEE 802.11(b, g, n, a, ax, ah) family of standards. WiFi comprises of wireless Access Point (APs) that uses ISM frequencies of 2.4/5.8 GHz to provide users /stations (STA) with wireless access to the internet.

Interference due to the spectral overlap between Wi-Fi and WSN channels and extreme proliferation of WiFi connectivity is a huge challenge for future networks. In comparison with WSN, higher powered WiFi signal exhibit highly dynamic channel characteristics as per WiFi usage (for example reading, streaming and audio streaming). Moreover it exhibits bursty transmission patterns that can easily corrupt WSN transmissions.

The effect of WiFi enabled radio over WSN and Bluetooth based devices is discussed in [34] and [35]. On selecting overlapping WiFi (2437 MHz) and WSN (2435 MHz) channels, WiFi reduces the throughput of WSNs by 22% while remaining unaffected by WSN transmissions. In contrast if the frequency separation between WiFi center frequency (2462 MHz) and WSN channel (2405 MHz) is adequate, no interference was reported. WiFi also degraded the performance of BL by reducing throughput by 36%. In return WiFi also faced a throughput reduction by 6% due to BL transmissions.

C. BLUETOOTH

Bluetooth (BL) [36] is a low powered device to device communication protocol also known as the IEEE 802.15.1 [37]. It is a Wireless Personal Area Network (WPAN) that uses low range radio links and a Master/Slave architecture. BL is used in many low powered devices such as

- Hearing aids [38], medical devices[3]
- Hands free, wireless audio headsets [39]
- Vehicle locking [40], vehicle stereo control
- PC to PC communication, Wireless mouse/keyboards/ printers
- Gaming consoles
- Industrial Bluetooth Mesh Networking [41]
- BL based direction finding for cm level positional accuracy [42], [43]
- Advertising services [44], [45]

Bluetooth Low Energy (BLE) is a variant of BL that uses 40 channel (2 MHz) as compared to 79 channels (1 MHz) of the classic BL. BLE is designed for prolonged low power operation and also supports for supports mesh networking.

The effect of low power signals of Bluetooth enabled devices on WiFi based devices is presented in [46]. The effect of BL interference on WSN is studied in [47]. Experimental analysis reported an increased PER (Packet Error Rate) by 60% (non-beacon enabled WSN) and 100% (beacon-enabled) due to BL.

TABLE 1. Wireless networks specifications.

Technology	WSN	WiFi 802.11b/g	WiFi 802.11a	WiFi 802.11n	BL IEEE 802.15.1	BLE	Microwave Owen	LTE-U
Frequency	868.3/902-928/2400-2483.5 MHz	2.4 GHz	5.8 GHz	2.4/5.8 GHz	2.4 GHz	2.4 GHz	2.45 GHz /915 MHz	3.5, 5 GHz
Channels	1/10/16	14	24	24	79	40	-	-
Bandwidth MHz	0.6/2/5	22/20	5/10/20	20/40	1	2	60	10/20
Modulation Scheme	BPSK/O-QPSK	BPSK-Barker, QPSK-Barker, QPSK-CCK /CCK, Barker, OFDM	OFDM	CCK, DSSS, or OFDM	GFSK, $\pi/4$ DQPSK, 8DPSK	GFSK	Can be modelled as a frequency sweeping AM-FM signal [51]	Same as LTE
Data Rate	20/40/250 Kbps	1,2,5.5,11 Mbps	6-64 Mbps	$\leq$ 600 Mbps	3000/2000/1000 Kbps	1000 Kbps	-	Same as LTE
Medium Access	CSMA/CA	CSMA/CA	CSMA/CA	CSMA/CA	FDMA and TDMA	FDMA and TDMA	-	LBT
Transmission Power	$\leq$ 0 dBm	$\leq$ 20 dBm	$\leq$ 20 dBm	$\leq$ 20 dBm	$\leq$ 10 dBm	$\leq$ 10 dBm	6 dBm to 33 dBm	23 dBm
Coexistence	Energy detection based CCA (Clear Channel Assessment)	Energy detection based CCA	Energy detection and Carrier Sense based CCA	Energy detection based CCA	FHSS	FFH and Channel Blacklisting	-	LBT
Communication Topologies	Star, P2P (Peer to Peer)	*Infrastructure*/BSS (Basic Service Set), *Adhoc*/IBSS (Independent BSS) and *Mesh*/MBSS)	Infrastructure (BSS), Adhoc (IBSS) and Mesh (MBSS)	Infrastructure (BSS), Adhoc (IBSS) and Mesh (MBSS)	Star	Star, Broadcast, Mesh	-	NA

D. MICROWAVE OWEN

Microwave Owen (MW Owen) is a household appliance used for cooking and reheating food. MWOs use magnetron tubes to generate RF (radio frequency) waves in the 2.4 GHz frequency band. It generates a 60 MHz wide signal synchronized with the AC mains frequency i.e. 50/60 Hz with a nearly 50% duty cycle. The spurious radio power leakage from MWOs in orders of 16 dBm to 33 dBm seriously interferes with low powered technologies in the ISM band.

The effect of MWO on BL is studied in [48] with results showing that MWO degrades the BL transmissions within a distance of 5m. In [49] the propagation characteristics of MWO are studied. Overall MWO interferences have known transmission patterns and often have short term occurrences as they are typically operated for several minutes for heating purpose.

E. LTE U

LTE (Long Term Evolution) is a 3GPP (3rd Generation Partnership Project) standard for cellular communication as proposed in 3GPP Release 8 utilizing licensed frequency bands as purchased by the service provider. To meet the exponential increase in cellular users and the high QoS requirements of voice and data, 3GPP is now leveraging the power of unlicensed spectrum.

LAA (Licensed Assisted Access) in Release 13 introduced the provision of offloading downlink data in unlicensed bands. Extended LAA in Release 14 extended this to uplink traffic as well. NR (New Radio) based Release 16 provides a new standalone mode of unlicensed spectrum usage without anchoring with a 4G or 5G licensed anchor. Release 17 proposes an advancement in the Enhanced Mobile Broadband (eMBB) to implement NR in the 52.6 GHz to 71 GHz band.

A study of LTE and WiFi interference is studied in [50] discussing the detrimental effects of greedy LTE transmissions on WiFi. Without scheduling or coping mechanism, LTE severely degrades WiFi transmissions.

A summary of these Wireless Network technologies with a detail comparison with respect to specifications is presented in Table 1.

III. CHALLENGES

A. SPECTRAL CONGESTION

With the massive proliferation of Wireless Networks and the upcoming IOT (Internet of Things) and 5G Networks, it is evident that many heterogeneous networks will coexist due to the scarcity of RF spectrum [52] as shown in Fig. 1. Existing ISM users include:

- Wireless Sensor Networks (WSN) based on ZigBee, 6LoWPAN, LoRa etc.
- Bluetooth and Bluetooth Low Energy
- WiFi (802.11) – 2.450 GHz and 5.800 GHz
- Wireless Local Area Networks

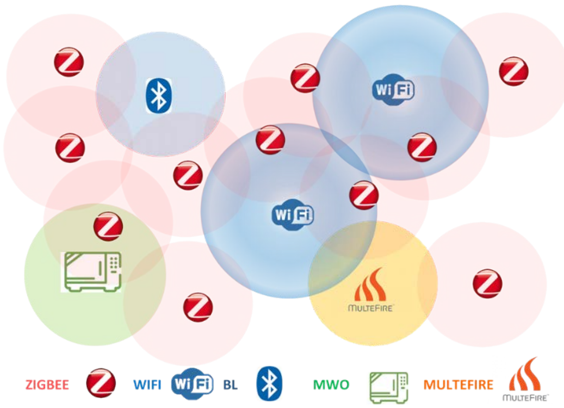

FIGURE 1. Collocated wireless networks.

- Microwave Owen
- Digital Enhanced Cordless Telecommunications (DECT) phones
- Pet trackers
- Automobile locking key

Future candidates for ISM band users would result in more congestion in the RF spectrum and new spectrum sharing paradigms as there is an increased motivation to leverage the unlicensed band to achieve QoS requirements. Several upcoming wireless technologies are discussed below:

- IoT (Internet of Things) is an all-encompassing framework comprising of a massive amount of heterogeneous sensors interconnected through the internet. IoT based applications include smart cities, smart homes, agricultural monitoring, traffic monitoring, weather monitoring etc.
- Internet of Medical Things (IoMT) is a sub category of IoT involving data acquisition from health sensors in hospital wards, at home patients, senior citizens' health monitoring etc.
- Internet of Industrial Things (IIOT) is a mission critical variant of IoT existing in manufacturing plants, grid monitoring applications etc. which requires high reliability and stringent time constraints. The key technologies used alongside IIoT are cloud computing, edge computing, machine learning etc.
- 5G New Radio (NR) is the improved radio access technology (RAT) using both 6 GHz and mmWave frequencies. With improved spectral efficiency, frequency reuse, enhanced OFDM modulation schemes, MIMO and beamforming, NR is expected to deliver the throughput and QoS requirements of 5G and beyond.
- NR-U (NR Unlicensed) [53] was proposed in 3GPP Release 16 that leveraged unlicensed bands for both uplink and downlink operations.
- CPS (Cyber-physical systems) are the next generation computing systems in which the computing elements interact with the physical components and they are interconnected with each other. The gathered data is shared with one another to make informed control decisions.
- UWB (Ultra wide band) is a short range data transfer protocol that uses a very low power, high bandwidth signal using frequencies between 3.1 GHz to 10.6 GHz and are capable of delivering high data rates.
- D2D-U (Device to Device) is a variant of D2D (device to device) communication which was proposed in 3GPP Release 12. D2D enables UE (User Equipment) to directly communicate with a UE in its vicinity without routing via a BS (Base Station) using licensed or unlicensed frequency bands. D2D-U uses unlicensed spectrum to achieve this one hop communication.

B. COMPLEX SPECTRUM

With diverse communication protocols and heterogeneous wireless networks being collocated as shown in Fig 2, the resulting spectrum is complex and dynamic. Wireless signal recognition techniques identify the technology type of all heterogeneous signals present in the spectrum by using frequency, bandwidth, modulation type and symbol rate estimation [54].

The effects of cross technology interference are asymmetric as the varying power levels of different wireless networks leave some technologies such as WSNs to be more vulnerable to interference.

C. EXISTING COEXISTENCE MECHANISM

There exists no inter technology coordination mechanism for efficient shared medium utilization.

D. WSN VULNERABILITIES

- Open Signal Structur
- Low powered node
- Coexistence with conventional/intelligent jamming signal

IV. MACHINE LEARNING

Machine Learning (ML) is an artificial intelligence (AI) technique that aims to replicate the human cognitive skills i.e. to study data and infer decisions based on its learning. The term ML was first used in 1959 [55] by Arthur Samuel from IBM in a study for a self-learning algorithm for learning a game of checkers. The algorithm was provided the rules and the directions and was trained within 8 to 10 hours of playing with a human. Sixty years of research has pushed the research boundaries even further and ML is amongst the driving forces of research in this era with applications ranging from bio medics, telecommunications, agriculture, finance, economics, language/speech recognition, behavior analysis, gameplay, search engine etc.

Survey in [56] is a comprehensive resource for ML related works in the context of wireless communications. A brief introduction to several ML algorithms is provided below.

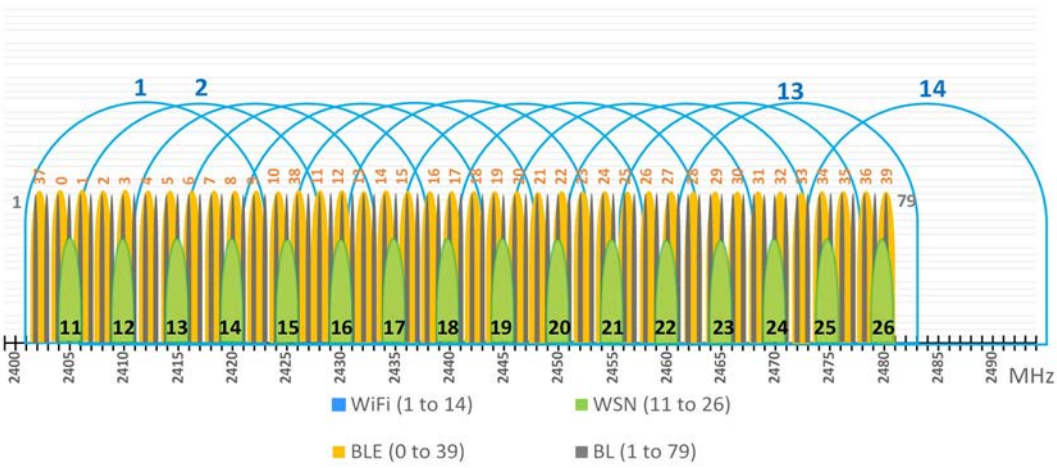

FIGURE 2. CTI in 2.4 GHz ISM band.

A. SUPERVISED LEARNING

Supervised Learning models use labeled/known data to train a model which then optimizes its performance by adjusting its weights in iterative learning cycles. Several supervised learning algorithms are discussed below.

- SVMs (Support Vector Machines) involve the mapping of n inputs into an n dimensional feature space with an appropriate hyperplane segregating different classes. The hyperplane can be a linear, radial or polynomial kernel that best separates all classes. The hyper parameter equation for SVM is given in Equation 1 in which w is the weight vector, b is the bias term and x is the input data.

$$w^T x + b = 0 \tag{1}$$

- KNN (K nearest neighbors) is a non-parametric algorithm that works on the basis of similarity/proximity of data belonging to the same class. Labelled data is plotted in an n-dimensional feature space. To classify a new sample, it is mapped in the feature space and its proximity to "k" neighbors on the basis of a distance metric such as Euclidean distance, Manhattan distance etc. is checked. The most prevalent class label amongst "k" neighbors is then assigned to the new sample on the assumption that same class label data lies in close proximity.
Consider a training dataset consisting of N training points (xn, yn) with x being the test sample and y being its class label. For a test sample to be classified, feature extraction is performed to calculate M features. To classify the signal, the distance calculation between test sample and train sample is done for all features. The distance formula can be Euclidean as in Equation 2 where xt_m is the test data, x_{nm} is the train sample and d_{euc} is the Euclidean distance. Or the Manhattan distance can be used as defined in Equation 3 where xt_m is the test data, x_{nm} is the train sample and d_{man} is the Manhattan distance.

$$d_{euc} = \sqrt{\sum_{m=1}^{M} (xt_m - x_{nm})^2} \tag{2}$$

$$d_{man} = \sum_{m=1}^{M} |xt_m - x_{nm}| \tag{3}$$

B. UNSUPERVISED LEARNING

Unsupervised Learning models use unlabeled/unknown data for training and self learns data characteristics and hidden relations and clusters data having similar features. Unsupervised learning comes in handy when unlabeled data is available. Several unsupervised learning algorithms are discussed below.

- K-Means Clustering algorithm clusters unlabeled data into k (a predefined value) clusters. All samples are mapped and initial cluster centroids are randomly initialized. Each sample point is associated with a cluster based on its distance with the centroids. After assigning all samples, the centroid is recalculated and adjusted and the process is iterated repeatedly till centroid location becomes fixed.
Clustering is done on the basis of Equation 4 where S is the cluster set, x is the input sample and x_{mean} is the mean of all samples in a particular S.

$$S_n = \mathrm{argmin}_{s_1,\ldots,s_K} \sum_{k=1}^{K} \sum_{x \in S} \|x - x_{mean}\|^2 \tag{4}$$

- GAN (Generative Adversarial Networks) generates data that resembles the unlabeled training data. GAN model is based on a Generator module that generates new samples and a Discriminator module that distinguishes between true and generated samples. It is a two person zero-sum game where in each iteration the discriminator is rewarded/unchanged for successfully distinguishing between true/fake samples or penalized for being fooled. Similarly the generator is also rewarded for fooling the discriminator or penalized conversely.

V. INTERFERENCE DETECTION

In order to manage CTI in any wireless network, comprehensive information of the spectrum at a given time is necessary. Interference identification is performed to identify signals of interest and interfering signals. All identified signals can be studied to infer their transmission patterns and spectral characteristics which then can be used intelligently in mitigating or avoiding interfering signals.

A. RSSI AND IQ BASED DETECTION TECHNIQUES

These techniques perform detection based on the raw radio sample received by the WSN receiver. Raw data maybe high resolution IQ (In-phase and quadrature) samples received from SDRs (Software Defined Radio). SDRs are high processing power radios that are used sparingly in most networks for resource rich task (such as Cluster Head (CH) operation, image processing etc.). Most WSN networks comprise of low power WSN motes that have limited sensing and signal processing capacity. Energy sampling in these low cost motes yields low resolution RSSI samples that are the highly filtered version of the IQ samples. An overview of both IQ and RSSI based techniques is provided in Table 2.

In [57], a lightweight interference detection algorithm is presented using signal bursts making this technique suitable for implementation on lower end resource constrained devices. Feature extraction for spectral, time domain and clear channel assessment (CCA) based features was performed. The classification task was performed via a multiclass support vector machine (SVM) and three variants of classification trees (CT) for accuracy comparison. The scheme was trained using real data collected in presence of varying interferers (single or multiple interferers present) and in varying environments such as varying node to interferer spatial distance and line of sight (LOS)/NLOS availability. The technique was validated using Contiki OS and WSN Crossbow motes. The proposed method achieved a classification accuracy of greater than 90%.

Authors in [58] are the first to use Deep Convolution Neural Networks (DCNNs) for Wireless Interference Identification (WII). To optimize the detection process on high resolution IQ data, the authors have used compressed sensing snapshots of IQ data belonging to WiFi, WSN and BL that are synthetically generated using VSG (Vector Signal Generator). Classification was performed via a CNN classifier and NFSC (neuro-fuzzy signal classifier) proving that the proposed CNN structure outperforms the NFSC by 8.19%. A classification accuracy of 95% was achieved on greater than −5 dB signal conditions.

The single class identification of [58] is modified to multi label classification in [59]. Each individual signal class (utilized signal) is augmented by adding a weighted sum of up to six interfering signals from the remaining classes. If same class interferers were added, WSN and BL achieved 100% classification accuracy as minimal spectral overlap is present within their channels. WiFi classification accuracy was 78% since there exists a spectral overlap within the considered bands. If different class interferers were added, WiFi and BL accuracy was 95% and WiFi accuracy was increased to 90%.

The data driven approach of [60] also uses deep learning (DL) for WII. WSN, WiFi and BL data is synthetically generated and classified via CNN. Three different signal representations i.e. raw IQ data alongside with its amplitude/phase notation and FFT (Fast Fourier Transform) notation are used for accuracy comparison. FFT signal representation performs the best giving a gain of 5% in moderate to high SNR (Signal to Noise Ratio) environment and a gain of 20% in low SNR environment.

Deep learning is used in [61] to identify good condition WSN signals from concurrent 802.11 beacon, 802.11 video, 802.11 file transfer, BLE, and microwave oven interferers. Real life collected data is trained on a custom CNN in Python. Micro level interference detection i.e. detection on a sample basis yielded 75%, 83%, 69%, 80%, 84%, 98% respectively. A Macro level classification is further proposed to fine tune the detection. The classification labels of samples in 10s macro were windowed to find the dominant interference leading to a classification accuracy of 93%. The thresholds for finding the dominant interference have been allocated as per experimental findings.

An optimization in the CNN structure of [58] is proposed in [62] alongside LSTM (Long short-term memory), ResNet (Residual Network) CNN and CLDNN (Convolutional Long-Short Term Deep Neural Network) based deep learning. All schemes except for ResNet yielded higher accuracy. Careful selection of band size resulted in training time reduction as overlapping classes are merged. Effect of training SNR value was also studied and found that CNN trained with −2dB data effectively classified data belonging to any SNR value while reducing the training time by 30 times.

RSSI based histogram features and RSSI time based features in [63] capture the distinctive characteristics of both streaming (LTE, DVBT-Digital Video Broadcasting Terrestrial) and non-streaming technologies (WiFi). A custom threshold based detection rule then identified the exact signal type. Results show that sub-nyquist sampling based RSSI (Received Signal Strength Indicator) samples yielded 92% accuracy which is promising to be implemented on resource constrained devices. PCA (Principal Component Analysis) and random sub sampling is also studied for reducing the dimensionality of data.

CTI detection in sub GHz ISM bands is studied in [64] targeting three LPWAN (low-power wide-area network) protocols that are IEEE 802.15.4, LoRa (Long range) and Sigfox. A spectrum manager framework is proposed that is trained offline to classify various technologies, create REMs (radio environment maps) of the environment and perform appropriate spectrum management decisions. Raw IQ data and its FFT representation are classified using a CNN. For low SNRs (less than 10 dB), FFT based classification is significantly superior keeping in mind FFT conversion does bear a processing overhead. However for SNRs above 10 dB, both raw IQ and FFT performed similar.

LTE TXOP (transmission opportunity) can be adjusted intelligently in presence of WiFi traffic. In [65] ns3 is used for generating test data of saturated and unsaturated Wi-Fi. Network is saturated when no increase in throughput occurs with the increase in packet arrival rate Based on traffic saturation status, optimal coexistence schemes can be applied. Frame and packet based features are used along with CNNs for classification.

In energy conservation WSN schemes using LPL (low power listening) and LPP (low power probing) rendezvous mechanisms, nodes are duty cycled i.e. periodically put to sleep and awakened on detection of WSN transmission. However they may be switched on inadvertently due to interference signals that are readily available in ISM bands. This false wake up issue is countered in Zisense [66] where RSSI is used to detect the presence of WSNs apart from interferers hence conserving energy, increasing PDR and reducing false wakeups.

SNR boosting has been proposed in [67] to fine tune the training process. Dataset of [58] is utilized which has been recorded for 21 SNR values. SNR bagging identifies the small subset of the SNRs that provide most optimal classification results for all test SNRs. Moreover due to smaller training dataset, training time is reduced by 30 times.

A study on interference effect on bit error rate and bit error locations has been done in [68] by using MATLAB generated WSN signals under the influence of three interferers. Interferers include CW (continuous wave) jammer (spurious radio signal), matched signal interference (intelligent jamming signal matched to the signal being transmitted) and WiFi signals. Using Monte Carlo simulations, the error free and erroneous packets were statistically analyzed and nine distinct features were identified and subsequently classified using an SVM.

Unsupervised learning self learns data classes of unlabeled data. Autoencoder based unsupervised signal classification is proposed in [69] that distinguishes LTE signals from anomalous signals present. Autoencoders are unsupervised ML algorithms that take unlabeled dataset, encode it to a compressed code and then aim to reconstruct the input data whilst learning the underlying data patterns. Three variants of autoencoders were trained with LTE signals and tested with LTE and WiFi signals. Resulting classification accuracy and low training time (47s) makes this approach practical for deployment in real life scenarios.

A spectral analysis framework for resource constrained edge devices is provided in [70]. PDF (Probability Density Function) based feature extraction is done for considered signal classes that are ZigBee (without interference) and ZigBee in presence of CW (Continuous wave) jamming signal, matched signal (deceptive jamming), thermal noise and WiFi signal. Resulting features are classified using SVM and Random Forest with SVM providing better accuracies and lower prediction time.

ADS-B (Automatic Dependent Surveillance-Broadcast) is an aeronautical surveillance system used by air traffic controllers to monitor signals transmitted by aircrafts regarding their velocity, position, identification etc. In [71], over the air ADS-B signals are captured and decoded to find the airplane IDs that are used as labels for the captured IQ radio sample. Six different ML and DL models are used for classification with CVNN (Complex Valued Neural Network) resulting in the highest classification accuracy of 99.8%.

B. SPECTRAL SIGNATURE ANALYSIS BASED DETECTION TECHNIQUES

Computer Vision (CV) techniques aim to mimic human vision by training systems to observe images and extract important information. Signals exhibit distinctive signatures when analyzed in frequency domain. Spectral analysis techniques yield snapshots of signal signatures that can be presented as an image classification task in CV.

In [72], Grad-cam architecture is used for classification between thirteen different wireless technologies. Signal collection was done via USRP (universal software radio peripheral) radio and 10ms observation window spectrograms were computed. Average classification accuracy of 94% was obtained.

Other spectral analysis techniques can be used for interference detection and identification (IDI) instead of basic spectrograms. Choi William Distributions (CWD) is used in [73] for signal spectral analysis. The CWD transforms of six different wireless signals including LFM (linear frequency modulated), Costas codes, BPSK, Frank, T1, T2, T3 and T4 signals are classified using a CNN. The overall classification accuracy is 93.7% for SNRs greater than and equal to -2 db.

An anomaly detector for a spectrum manager is proposed in [74] to identify anomalous signal behavior such as the absence of a legitimate signal or the sudden appearance of an unwanted signal. Interpretable features such as signal bandwidth, class etc. are used by the Adversarial Auto Encoder (AAE) to recreate the signal and localize any anomaly present. AAE is used as a reconstruction based anomaly detector which is useful for comprehensive spectrum monitoring to detect missing transmissions, out of band spurious signals, high transmit power signals etc. for each band. Moreover WII using AAE yielded 100% classification accuracy.

IDI using spectrograms and deep learning in ISM can be extended to all radio bands facing the same issue of concurrent interferers. Spectrogram based interference detection is implemented in [75] for an LTE cellular service provider. Eight known LTE signal interferers are identified arising from external/atmospheric, inner LTE system and inter cellular system based sources. This is a routine time consuming task for cellular engineers to manually label these interferences.

TABLE 2. RSSI and IQ based detection.

Method	Signal Classes	Dataset	Feature Set	Classifier	Time (Constraint to hardware)	Accuracy	Year
Real-time Interference Identification via Supervised Learning [57]	IEEE 802.11b/g/n IEEE 802.15.4 IEEE 802.15.1 BLE	Real RSSI Samples captured using TelosB WSN motes and Intel AC7260 802.11 NIC card	Spectral Features (channel number) Time Domain Features (Burst length, Burst mean power, Crest factor, Envelope ripple) CCA Mode	Classification Trees RFCT Multiclass SVM	Testing Time 620 us	90%–97%	2018
Wireless Interference Identification with Convolutional Neural Networks [58]	IEEE 802.11 b/g (3 channels) IEEE 802.15.4(2 channels) IEEE 802.15.1(10 channels)	Synthetic Compressed sensing IQ snapshots generated using VSG SMBV100A and RSA6114A Spectrum analyzer Post processed data for 21 different SNR levels	NA	CNN NFSC	Training time 20 ms	>95% (SNR>= -5 dB)	2017
Multi-Label Wireless Interference Classification with Convolutional Neural Networks [59]	IEEE 802.11 b/g (3 channels) IEEE 802.15.4 (2 channels) IEEE 802.15.1 (10 channels)	Dataset same as [58] Multi-label signals generated by adding signals	NA	CNN	Training time 390s per epoch	IEEE 802.11(90%) IEEE 802.15.4(95%) IEEE 802.11(95%)	2018
End-to-End Learning From Spectrum Data: A Deep Learning Approach for Wireless Signal Identification in Spectrum Monitoring Applications [60]	IEEE 802.11 b/g (3 channels) IEEE 802.15.4 (2 channels) IEEE 802.15.1 (10 channels)	Same as [58] Crawdad Dataset in FFT, IQ and Amp-Phase representations	NA	CNN (IQ) CNN (Amp Phase) CNN (FFT)	Training time 60s per epoch	At -10 dB CNN-IQ (76%) CNN-Amp Phase (80%) CNN-FFT (85%)	2018
Interference Source Identification for IEEE 802.15.4 Wireless Sensor Networks Using Deep Learning [61]	802.15.4 Wi-Fi beacon Wi-Fi video streaming Wi-Fi file transfer BLE iBeacon MWO	Real RSSI dataset collected through real signals using CC2530 802.15.4, TL-WN722N WiFi, TI-CC2540 BLE and MWO.	NA	Micro level classification via CNN Macro level classification via rule based labelling window	Testing time 1ms per sample	93% f-measure	2018
Deep Learning for Interference Identification: Band, Training SNR, and Sample Selection [62]	IEEE 802.11 b/g (3 channels) IEEE 802.15.4 (2 channels) IEEE 802.15.1 (11 channels)	Same as [58] Crawdad Dataset in FFT, IQ and Amp-Phase representations	NA	CNN LSTM ResNet CLDNN	Average Training time(108s)	89.5%	2019
Wireless Technology Recognition Based on RSSI Distribution at Sub-Nyquist Sampling Rate for Constrained Devices [63]	Wi-Fi (5540 MHz) LTE (806 MHz) DVB-T (482 MHz) LTE + WiFi	Real RSSI dataset captured using USRP radios with real LTE Base station, DVBT station and WiFi AP	Standard Deviation No of peaks Average power level Visible noise peak	Decision based on learned thresholds	-	92%	2017

TABLE 2. *(Continued.)* **RSSI and IQ based detection.**

A Convolutional Neural Network Approach for Classification of LPWAN Technologies: Sigfox, LoRa and IEEE 802.15.4g [64]	Sigfox LoRA IEEE 802.15.4 Interference Class (Sigfox and LoRa, LoRa and 802.15.4, 802.15.4 and Sig, 802.15.4 and Sigfox and LoRa)	Real dataset captured using Sigfox, LoRA and IEEE 802.15.4g transmitters and a B200mini USRP board.	NA	CNN trained on IQ CNN trained on FFT	-	CNN-IQ (95%) CNN-FFT (97%)	2019
Machine Learning Enabled Wi-Fi Saturation Sensing for Fair Coexistence in Unlicensed Spectrum [65]	LTE-U WiFi Saturated WiFi Unsaturated	Synthetic data generated using NS-3 used to model a WiFi network having 1 access point with varying values of • No of active nodes • Packet length • Contention window • Packet arrival rate	histogram of Inter-frame Spacing (H-IFS) average duration of IFS (AD) collision percentage (CP)	CNN (H-IFS) CNN (H-IFS and AD) CNN (H-IFS,AD,CP)	-	96%	2021
ZiSense: Towards Interference Resilient Duty Cycling in Wireless Sensor Networks [66]	ZigBee WiFi BL MWO	Real dataset captured using TelosB motes, LAN Traffic V2 on a laptop, BL headset and a microwave.	On Air time Min Packet Interval Peak to average Power Ratio Under noise floor	Rule based detection	-	97.3% True Positive Rate (WSN)	2014
Efficient Training of Deep Classifiers for Wireless Source Identification using Test SNR Estimates [67]	IEEE 802.11 b/g (3 channels) IEEE 802.15.4(2 channels) IEEE 802.15.1(10 channels)	Dataset same as [58]	NA	CNN ResNet CLDNN	Training time reduced by 30 times due to SNR bagging	100% (At 20 dB)	2020
Identifying Distinct Features based on Received Samples for Interference Detection in Wireless Sensor Network Edge Devices [68]	ZigBee and CWJ ZigBee and matched signal ZigBee and WiFi	MATLAB simulation	PDF features (area between bins, averaged area of bins, non-zero bins, maximum peak) Derived features (Variance, standard deviation, entropy, mean value, maximum value)	SVM	-	4.4508% test data error for SNR> 5dB	2020
Towards Enhancing Spectrum Sensing: Signal Classification Using Autoencoders [69]	LTE WiFi (802.11ax) WiFi (802.11ac)	Real LTE signals (USRP SDR and GNU Radio toolkit) and synthetic WiFi signals (MATLAB WLAN toolbox)	I component Q component Amplitude value Phase value	Deep auto encoder Variational auto encoder LSTM auto encoder	Training time 47s (Deep auto encoder)	99.98% (Deep auto encoder)	2021
Developing Novel Low Complexity Models using Received In-phase and Quadrature-phase Samples for Interference Detection and Classification in Wireless Sensor Network and GPS Edge Devices [70]	ZigBee ZigBee and CWJ ZigBee and matched signal ZigBee and WiFi ZigBee and thermal noise	Real ZigBee signals (DIGI XBee nodes) and interferers (Pluto SDR and MATLAB)	PDF features (area between bins, averaged area of bins, non-zero bins, maximum peak) Derived features (Variance, standard deviation, entropy, mean value, maximum value)	SVM Random Forest	-	98%	2021

TABLE 2. ***(Continued.)*** **RSSI and IQ based detection.**

Large-scale real-world radio signal recognition with deep learning [71]	ADS-B signals	Real signal collected using SM200B SDR and an HP Laptop	IQ samples for DL models Bi spectral transform features for ML models	DL models (CNN, LSTM and CVNN) ML models (KNN, Decision Trees and SVM)	-	99.8% (CVNN at 20 dB)	2021

Labelled dataset provided by a cellular company was processed for spectrogram analysis and classification performed using AlexNet yielding 95% accuracy.

The spectrum aware framework proposed in [76] identifies all signals present to assist spectrum managers in optimizing spectrum sharing. A manual feature extraction via RSSI histogram based features was performed and classified via a Fully Convolutional Neural Network (FCNN) and a combined Decision Tree (DT) and Random Forest (RF) based classifier. Automatic features were detected via three CNNs using raw IQ data, RSSI data and spectrograms. The CNNs trained on spectrograms and IQ based data yielded highest classification accuracy.

In [77] deep convolutional networks are used for spectrum monitoring in radar bands. The scope of this work was to detect whether a radar signal is present (with or without interferers) or absent (only interferers present) via CNNs. The spectrum monitoring network may aggregate these measurements to create spectral occupancy maps that would help in identifying secondary users and their transmission patterns. A classification accuracy of 98.6% was achieved using a signal spectrogram based CNN which was further improved to 99.6% using a composite amplitude and phase data representation of the same IQ data. Note that standalone amplitude and phase data representations performed poorly.

Recent developments for Citizens Broadband Radio Service (CBRS) suggested the use of 3.5 GHz (3550-3700 MHz) band which is originally being used by federal occupants such as US ground and ship based radars and SPN-43 air traffic radar. The proposed architecture uses environmental sensors to detect radar presence and a spectrum access system to coordinate CBRS transmissions in contrast to the high priority radar transmission. In [78], IQ data from antennas capturing radar and CBRS transmissions is collected and spectrograms are computed. A variety of classification schemes are used. Classical techniques included energy based detection which sums the energy across a time period and sweep integrated energy detection which extracts the peaks (highest SNR portion of the signal) followed by energy detection. Machine learning techniques included SVM, KNN (k-nearest neighbors) and GMM (Gaussian mixture model). Moreover, amongst the six deep learning models used for classification, Inception V1 performed the best. Overall a custom defined CNN yielded the highest classification accuracy of 99.7% amongst all techniques compared.

In [79], cellular signals were detected via cyclo stationary analysis based spectral correlation function (SCF). Real life data collection of GSM, UMTS, and LTE signals at receivers placed in sub-urban areas was done. In the first experiment, GSM, UMTS, LTE and AWGN samples were converted to SCF representations and classified using a CNN. The results reported a lower classification accuracy of 92% which is due to the misclassification of low SNR signals as noise signals. Hence a two part solution was proposed, initially a spectrum sensing task was done to assess if signal is present (Class 1) or not (Class 0). For Class 1 dataset, all signals classes were merged as one class and the remaining AWGN samples were assigned to Class 0. This spectrum sensing gave an intermediated classification accuracy of 96%. A subsequent CNN trained on separate UMTS, LTE and GSM signals resulted in 98.5% accuracy. A study of data representations of IQ samples (FFT, Amplitude Phase and SCF) was also done with SCF being the best representation. Proposed CNN also performed better than an SVM and various DL algorithms that were trained with a reduced SCF (R-SCF) notation.

A novel spectral analysis technique called quarter- spectrogram (Q-spectrogram) is proposed in [80]. Single label data of LTE, WiFi, FBMC and radar and their multi-label combination signals were captured and spectrograms were generated. A condensed spectrogram was created by extracting two vertical sections containing most information from the normal spectrograms (128 × 128 pixels) and concatenating them horizontally. This reduced image was then vertically split and the sections are concatenated horizontally. Resulting Q-spectrograms (64 × 64 pixels) are quarter the size of the original spectrogram and are information dense. The resulting data was classified using various deep learning models.

The detection of signal and interference is a multi-label task. For a study involving multiple signals, single label signals (one signal at a time) as well as mixture signals (all possible signal combinations of single-label signals) have to be generated which is a cumbersome task. In [81], a discriminative dictionary learning (DL) algorithm is proposed for the multi label signal identification by using single label data (BL, BLE, FHSS1, FHSS2, WiFi1, WiFi2). The learned features are classified using ZF (zero-forcing), MF (matched filter), LR (logistic regression), SVM and

NN (neural network) classifiers resulting in the probabilities of each signal class present.

A combined CNN and LSTM architecture is proposed in [82] using both raw I/Q signals samples and their spectrograms. The CNN captures the visual spectral signatures present in the spectrograms whereas the LSTM extracts the time-series signal characteristics of the raw I/Q signal. By integrating the FDA (frequency domain analysis) with the conventional raw radio signal analysis, a 10% increase in classification accuracy is achieved.

An overview of spectral analysis based technique overview is provided in Table 3.

VI. COEXISTENCE MECHANISMS

With the current and envisioned future signals operating in ISM bands, more robust coexistence mechanisms need to be designed to counter the deficiencies of the existing coexisting methods. Interference awareness needs to be introduced instead of using generic coping mechanism to most efficiently counter each type of interference.

A. SOFTWARE BASED MECHANISMS

A survey of software based coping mechanisms is provided below in which modifications to the protocol stack is proposed.

An interference detection and coping mechanism is proposed in [83] as each interference calls for a unique mitigation solution as per its transmission characteristics. Received RSSI samples are quantized to four power levels. Consecutive samples having same power level are represented in a compressed form using run length encoding. Resulting sequence is analyzed to determine legitimate bursts. All detected burst are clustered using k-means to validate the interference specific cluster formations. The trained model is tested in a real office environment yielding 90% classification accuracy. The Chrysso protocol which ordinarily performs channel switching in presence of interferers is modified to use Specksense for channel blacklisting. The proposed Specksense integrated Chrysso solution outperforms the regular Chrysso by 30% increased PRR.

SoNIC [84] uses a reactive interference detection scheme triggered on received corrupted packets. Six packet based and RSSI based features are calculated and classified via SVMs and DTs.

TIIM [85] normally operates in passive mode performing basic link quality monitoring and RSSI variance check. On detecting interference, it switches to the active mode and subsequently packet and time based features are calculated. Instead of explicitly identifying the interferer type, TIIM simply learns channel characteristics that could be best countered using known coping mechanisms. For each signal observation, all coping mechanisms are simulated and the optimal cost-benefit technique is selected.

A statistical analysis of WiFi packet arrival demonstrated that WiFi packets are highly clustered [86] and having white spaces in between that can be utilized opportunistically by WSNs. A pareto model based white space estimation of WiFi is done by WSN nodes and the most optimal frame size is adapted to achieve best throughput in the remaining whitespace duration. Results showed the proposed protocol WISE outperformed B-MAC and OppTx whilst having considerably low overhead.

A simple IDI (Interference detection and identification) is proposed in [87] that uses RSSI based feature extraction (maximum channel usage duration, maximum channel clear duration, channel usage ratio/active ratio, signal periodicity). This lightweight IDI in combination with decision tree (DT) based classification yielded 95.24% accuracy. Proposed scheme consumed less memory when compared with an FFT based feature extraction and decision tree solution (14% less) and another solution using the same lightweight feature extraction with logistic regression (3% less). Depending upon the type of interference, distinctive coping mechanisms are proposed but not implemented.

Crosszig [88] is a combined IDI and coping solution. It detects interference using physical layer features. It introduces a minimal amount of error correction code. On encountering long burst errors, Maximum Ratio Combining (MRC) based packet recovery is done. If high packet failures occur, a Reed Solomon (RS) code based redundancy is triggered which is adaptive as per packet reception ratio (PRR) hence adding optimal redundancy only. The scheme is validated against a fixed RS, adaptive RS and a packet merging based scheme. Crosszig intelligently outperforms these three schemes as per the interference level whilst keeping the code overhead low.

Bursty WiFi traffic introduces burst corruptions in WSN data which is difficult to correct by traditional forward error correction (FEC) due to the presence of consecutive errors present in one block while other blocks remain error free. This results in a high decoding delay and waste of redundancy. ZiXor [89] is a modified FEC scheme that uses modulo-k XOR operations. If k black redundancy is added, starting from 1^{st} bit, all k-apart bits are XORed and form 1^{st} redundant bit and so on. This ensures that each bit of an error burst are mapped to a different redundant block making recovery possible. Amount of redundancy is adaptively configured as per historic calculated block error rate. Moreover, if non bursty errors are dominant, system switches to fountain codes.

BuzzBuzz [90] studied the effect of simultaneous WSN and WiFi transmissions and realized the concept of interference domains. If WiFi and WSN are far apart (for e.g. 115 m) it is in asymmetric interference region where WiFi dominates and corrupts WSN thus requiring FEC. However in case of symmetric interference domain caused by WiFi and WSN being close (less than 15m), WSN can trigger WiFi to back off introducing errors in header only causing retransmission of entire packet. Proposed solution uses multi headers (MH) i.e. an extra header/preamble is added in the payload which is then preceded with another header. In the event of symmetric interference region, all corruptions would occur in the first

TABLE 3. Spectral signature analysis.

Method	Signal Classes	Dataset	Feature Set	Classifier	Time (Constraint to hardware)	Accuracy	Year
Spectral Detection and Localization of Radio Events with Learned Convolutional Neural Features [72]	ATSC ISM(Bluetooth, WiFi) LTE UL LTE DL DVBT WiMAX FM GSM DL GSM UL TETRA P2P P25	Real radio spectrum data-RSSI sample captured using USRP board	NA	VGG CNN	Training time(10 min for 200 epochs) Classification time(1.5ms)	94%	2017
Convolutional Neural Networks for Automatic Cognitive Radio Waveform Recognition [73]	BPSK LFM Costas codes Frank code T1-T4	Synthetically generated in MATLAB with different values of SNR	Choi William Transform followed by image post processing	CNN	-	93.7% (At SNR>= -2 dB)	2017
Unsupervised Wireless Spectrum Anomaly Detection with Interpretable Features [74]	GSM, LTE, TV broadcast signals in 800 MHz , 900 MHz and other sub GHz bands	Used real HackRF SDR Dataset, Electrosense Dataset and a synthetic dataset	Spectrograms	Adversarial auto encoders	Classification time (0.91 micro sec)	Approximately 100%	2019
Using Deep Convolutional Neural Network to Recognize LTE Uplink Interference [75]	DECT Neighbor UE TDD Asynchronous. TDD Ultra-far GSM Spurious, GSM Inter-mod LTE Spurious MMDS	Real Dataset provided by a Chinese cellular company	Spectrograms	AlexNet	NA	95%	2019
Towards low-complexity wireless technology classification across multiple environments [76]	Wi-Fi LTE Digital Video Broadcasting Terrestrial (DVB-T)	Real dataset (Publically available) captured using USRP radios with real LTE Base station, DVBT station and WiFi AP	Histogram distribution features for Manual feature	**Manual features** Fully connected Neural networks Random Forests Decision Trees **Auto feature extraction** RSSI CNN IQ CNN Image/Spectrogram CNN	Training time 51s 19s 100s 1500s 950s	87.2% 88.0% 95.3% 97.8% 97.1%	2019
Spectrum Monitoring for Radar Bands using Deep Convolutional Neural Networks [77]	Radar signal identification in presence of interferers commercial Long-Term Evolution (LTE) 906 MHz WLAN-2.462 GHz Interferers present in 0 to 5 GHz band *Class 0 –Radar Present* radar-only radar and WLAN radar and LTE samples. *Class 1-Radar not present* LTE-only WLAN-only Noise.	Real Dataset using USRP N210 RADAR TXM and a USRP N210 measurement capable device in the 0.906,2.4 and 2.3 GHz band	Spectrograms	CNNs trained on Spectrograms Amplitude Phase	-	99.6%	2017

TABLE 3. ***(Continued.)*** **Spectral signature analysis.**

Deep Learning Classification of 3.5 GHz Band Spectrograms with Applications to Spectrum Sensing [78]	SPN-43 Radar3 OOBE SPN-43 and Radar3 OOBE Neither	Real dataset collected using an omnidirectional antenna and CBS antenna	Spectrograms	Energy detection Sweep based detection SVM KNN GMM VGG-16 VGG-19 ResNet-18 ResNet-50 Inception-V1 DenseNet-121 Custom CNN LSTM	Detection time ED (0.4ms) Custom CNN (1.89ms)	CNN (99.7% in FROC)	2019
Spectrum Sensing and Signal Identification with Deep Learning based on Spectral Correlation Function [79]	GSM UMTS LTE AWGN	Real measurements collected using receivers, Rohde Schwarz FSW26 spectrum analyzer and Yagi antennas are employed at the receiver	SCF Amplitude Phase FFT	CNN (SCF) SVM (SCF) CNN (R-SCF) LSTM (R-SCF) DenseNet (R-SCF) CLDNN (R-SCF) ResNet (R-SCF)	CNN Training time per Epoch (60 s)	98.5% (at 9 dB)	2021
Shared Spectrum Monitoring using Deep Learning [80]	LTE Radar WiFi FBMC LTE + Radar LTE + WiFi FBMC + Radar FBMC + WiFi WiFi + Radar Noise	Real LTE and WiFi samples Radar, LTE and FBMC samples generated using USRP radios	Q-Spectrogram	AlexNet VGG 16 ResNet18 SqueezeNet InceptionV3 ResNet50	ResNet50 prediction time (Nearly 240 ms)	98% (ResNet50)	2021
Robust RF Mixture Signal Recognition Using Discriminative Dictionary Learning [81]	Wi-Fi (high occupancy) Wi-Fi (low occupancy) Bluetooth BLE FHSS1 FHSS2	WiFi, BL and BLE Signals generated using VSG. FHSS signals generated using drone controllers	Deep Scattering Spectrum features	SVM CNN ZF MF LR NN	-	ZF with Algorithm-3 provided best AUC (area under curve)	2021
Signal Detection and Classification in Shared Spectrum: A Deep Learning Approach [82]	Wi-Fi LTE 5G Wi-Fi + LTE Wi-Fi + 5G LTE + 5G Wi-Fi + LTE + 5G.	Signals generated and received using USRP radios	IQ samples Spectrograms	CNN + LSTM CNN LSTM SVM RF	-	92% (Spectrograms trained on CNN + LSTM)	2021

preamble, next preamble/last bytes would be uncorrupted hence requiring no retransmission.

In Smoggy link protocol [91], an IDI using short term and long term features are calculated that are studied to be resilient in static/no mobility, environment mobility, micro interference mobility and macro interference mobility. Since cross technology interference is asymmetric, burst probing is done to estimate PRR on an outgoing link. Resulting link map is used to find the best link available. Moreover black/white space of each interferer is modeled using a Pareto model and transmissions are scheduled accordingly to enable concurrent transmission.

Coexistence for WiFi and LTE-U is proposed in [92]. Traditionally LTE-U's coexistence algorithm opportunistically transmit on the most free channel The duty cycle of LTE-U and Wi-Fi is optimized and adaptively adjusted by the Q-learning, so as to improve the performance of the system by allowing LTE-U to occupy the appropriate time slots on multiple unlicensed channels.. Using Q-learning, the ON/OFF sequences of the WiFi on different channels were estimated and busy channels were opportunistically used for communication. The proposed scheme is compared with traditional algorithm, average algorithm, LBT (Listen before Talk) algorithm and CSAT (Carrier-Sensing Adaptive Transmission) algorithm with the proposed algorithm yielding the highest throughput and fairness factor.

mLTE-U [93] provides coexistence between LTE-U and WiFi collocated networks. Raw IQ radio samples are classified using a CNN to distinguish between LTE and WiFi symbol as well as multiple concurrent LTE signals, multiple concurrent WiFi signals and simultaneous LTE and WiFi signals which cause hidden terminal problem. mLTEU monitors the channel occupancy of each technology and adaptively assign best TXOP (transmission opportunity) period and subsequent muting period to ensure fair spectrum sharing.

In [94], a spectrum aware channel blacklisting mechanism was proposed for industrial internet of things (IIoT) systems that have stringent QoS requirements. The ever growing demand for unlicensed spectrum usage has threatened IIoT systems that share the spectrum with other wireless systems and are also susceptive to RF jamming and electrical interference from surrounding devices and equipment. This coupled with the fact that most IoT nodes are low complexity resource constrained nodes for which suitable interference detection schemes have to be devised. The proposed method performs real time spectrum estimation using intra-burst sampling pattern (IBSP) which is then used for channel blacklisting. The busy channels are then catered for in the next channel hopping sequence.

The LTE-U system uses unlicensed frequency bands in downlink mode for bandwidth hungry applications. Since LTE-U and WiFi both share the unlicensed spectrum, the LTE-U signals will adversely affect WiFi signals whose carrier sense medium access will force it to back off. To achieve fairness between LTE-U and WiFi transmissions, the work in [95] performs WiFi interference detection for all LTE-U users through clustering based on CQI (Channel Quality Indicator) and user location. The CQI would reflect the effect of interference caused by ongoing WiFi transmissions whereas node location is also a significant parameter for clustering as nearby nodes are likely to be facing the same interference levels. The coping mechanism is an optimal power and carrier allocation strategy. The LTE BS (base station) allocates QCI (QoS Channel Indicator) values depending upon the user's traffic. As per the QoS requirement of the user, the data is optimally distributed using licensed and unlicensed band for example a QCI of 1 is allocated if control data is being transferred (licensed carrier). Results prove that the proposed technique resulted in the increase in downlink throughput.

In coordinated LTE-U and WiFi coping mechanisms, information sharing between the two are provisioned via a protocol. In [96], an uncoordinated LTE-U and WiFi coexistence is proposed which requires modification to the LTE site and does not require any collaboration between the two technologies. The LTE contains a technology detection unit that classifies raw radio samples using CNN. By analyzing the IFS (inter frame spacing), the WiFi is said to be saturated i.e. maximum throughput has been achieved or inversely unsaturated. The most optimal LTE ON-OFF durations are adapted using rule based and Q-learning based algorithms. Apart from regular Q-learning, ER (Experience Replay) based Q-learning is proposed in which the Q-table is updated on the basis of 'n' historic experiences. Furthermore a RER (Reward Selective Experience Replay) based Q-Learning is also implemented in which 'n' historic experiences with the highest reward are considered for updating Q-table. Results show the RER scheme performed the best.

D2D-U is a variant of D2D that uses unlicensed spectrum to communicate in a one hop fashion with other UEs in a cell. In [97], D2D-U coexistence with concurrent WiFi transmission is proposed as its effect on existing legacy wireless networks is harmful. An LBT (Listen before Talk) scheme is proposed in which the D2D users will perform CCA. If the CCA determines the channel is already occupied, the D2D user will back off for a certain time and retry. This scheme ensure a high WiFi throughput while the D2D throughput is limited. Moreover, duty cycling based scheme can also be used that uses a fixed transmission duty cycle and favors the D2D system. A mode selection is done between the two proposed coping mechanisms for optimal performance based on WiFi traffic loads.

An overview of discussed techniques is provided in Table 4.

B. HARWARE BASED MECHANISMS

Hardware based techniques require modifications to the node hardware such as the requirement of special antennas or the use of additional helper nodes to manage the network.

A CCP (Central Coordination Point) and SNMP (Simple Network Management Protocol) based coexistence is proposed in [98]. The CCP performs WII using a SSU (spectral sensing unit) that characterizes interference using NFSC. The CCP is connected via an Ethernet backbone to all WT (Wireless Technology) masters of each heterogeneous network. CCP uses SNMPv3 as the management protocol. The defined MIB (Management Information Base) manages the spectral, temporal, spatial resources of all WTs. Coexistence amongst technologies is solved as an optimization problem to ensure minimal or no overlap in frequency, time and spatial domain. The scope of this work was to demonstrate the use of SNMP based CCP and a study of channel switch time, reconnection time and failed reconnects was done.

A CCP [99] is a management entity that uses dedicated control channels to communicate with all heterogeneous wireless networks. CCP performs environmental monitoring by sensing spectral emissions. Based on the radio environment, it perform optimal resource allocation to each heterogeneous wireless networks using Q-learning. Simulation using WSNs in presence of static interferer (like WLAN) and a frequency hopping (FH) interferer (like Wireless HART) show promising results.

In [100] a modified Coexistence Aware Clear Channel Assessment (CACCA) is proposed for WiFi to make it sensitive to WSN traffic. Proposed MF (matched filter) based CACCA that used the OQPSK filter (WSN specific) outperformed the simpler ED (energy detection) based CACCA, although both were deemed ok to use. Results show the increase in WSN throughput due to WSN aware CCA of WiFi.

TABLE 4. Software based coping techniques.

Method	Signal Classes	Dataset	IDI Details	Coping Mechanisms	Performance	Overhead incurred	Year
Detecting and Avoiding Multiple Sources of Interference in the 2.4 GHz Spectrum [83]	IEEE 802.11b/g/n 802.15.4 802.15.1	Real Data set captured using CC2420 radio in a WSN testbed with WiFi and Bluetooth interferences	K Means clustering algorithm	Interference detection Channel Blacklisting	IDI Detection rate (90%) PRR (Increase by 30%)	-	2015
SoNIC: Classifying Interference in 802.15.4 Sensor Networks [84]	WiFi Microwave Bluetooth Non interfering weak link	Real Data set captured using TelosB Motes and interferers in anechoic chamber	RSSI based features and Decision Trees	Spectral retreat (WiFi) Packet Scheduling (Microwave)	IDI Detection rate (87.5%) PRR (Increase by 16.4%)	-	2013
TIIM: Technology-Independent Interference Mitigation for Low-power Wireless Networks [85]	802.11 BL Cordless phone FHSS Cordless Wireless camera Microwave	Real Data set captured using WSN nodes and real interferers	Packet Statistics and Energy based features and Decision Tree based classification	Reed-Solomon Forward Error Correction (FEC) Reed-Solomon RSSI-based Packet Recovery (PM) Adaptive CCA threshold Channel Switching or No Action	IDI Detection rate (92%) PRR (Increase by 30%) Good adaptability to the dynamic channel	Implementation cost/bit overhead (5.6%)	2015
Beyond Co-existence: Exploiting WiFi White Space for ZigBee Performance Assurance [86]	WiFi WSN	Real Data set captured using TelosB Motes and Intel Atheros NIC based WiFi interferer in office environment	WiFi Whitespace detection by channel sampling to train a pareto model for white space characterization	Adaptive packet size based on White space duration to opportunistically utilize whitespaces	Frame delivery Ratio(Increased by 2x,4x as compared to B-MAC and OppTx)	Implementation Overhead(10.9% of B-MAC, 39.5% of OppTx)	2010
Machine learning based lightweight interference mitigation scheme for wireless sensor network [87]	WiFi Microwave Bluetooth	Real Data set captured using WSN nodes and real interferers	Channel utilization based feature extraction and classification using Decision Tree and Logistic regression model	WiFi (Spectral retreat) Microwave (Packet Scheduling) Bluetooth(Retransmit if no ACK is received as sporadic interference faced due to AFH of BL)	IDI Detection rate (95.24%) Memory consumption (Decreased by 14% and 3% as compared to FFT-DT and LW-LG)	Nil	2020
CrossZig: Combating Cross-Technology Interference in Low-power Wireless Networks [88]	WSN 802.11 (Light and Heavy traffic) Wireless camera (WC) MWO WC+ MWO WC + MWO + WiFi-Light WC+ MWO + WiFi-Heavy	Real data generated using USRP SDR and GNU Radio	Physical Layer features (Hamming distance, Signal Power and Demodulation Soft Values)	Packet Merging Adaptive Reed Solomon Code	IDI Detection rate (94.3%) Good put (Increased) Overhead (4.6% less than considered schemes) PRR (Provides high PRR for same level of redundancy added)	Approximately 1-12 FEC bytes per packet	2016
Embracing Corruption Burstiness: Fast Error Recovery for ZigBee under Wi-Fi Interference [89]	WiFi WSN	Real dataset captured using TelosB Motes and WiFi Laptop	IRS based packet error detection	Zixor FEC Fountain codes	Throughput (Increased by 47%) Latency (Decreased by 22%)	Minimal overhead incurred	2017

TABLE 4. ***(Continued.)*** **Software based coping techniques.**

Surviving Wi-Fi Interference in Low Power ZigBee Networks [90]	WiFi WSN	Real dataset captured using TelosB motes and WiFi AP	Channel quality estimation using packet loss	Hamming Codes or Reed Solomon Codes Multi Headers	PDR (Increased by 71%) Unacknowledged packets (Reduced by 50%)	-	2010
Exploiting Interference Fingerprints for Predictable Wireless Concurrency [91]	WiFi WSN Bluetooth	Real dataset generated using TelosB motes	Time domain and Frequency Domain features and city block based identification	Packet scheduling in whitespaces	Throughput (More than Beacon/CSMA On scheme)	Overhead (Lower than Beacon/CSMA On scheme)	2021
LTE-U and Wi-Fi Coexistence Algorithm Based on Q-Learning in Multi-Channel [92]	WiFi LTE-U	Synthetic data generated using MATLAB	NA	Q learning based modelling of WiFi whitespaces and LTE packet scheduling	Throughput (High) Fair factor (High)	-	2018
Enhancing the Coexistence of LTE and Wi-Fi in Unlicensed Spectrum Through Convolutional Neural Networks [93]	WiFi LTE Multiple LTE transmissions Multiple Wi-Fi transmissions Concurrent LTE and Wi-Fi transmissions.	Data captured using a controlled environment LTE n/w deployed on USRP radios and srsLTE software at 2.437 GHz WiFi (802.11g) on Zotac nodes using 2.4GHz 1 USRP radio deployed to collect I/Q samples	RSSI data in IQ and FFT formats classified using CNN	Adaptive LTE TXOP and Muting as per the detection of cross technology interference	IDI Detection rate (SNR>40 dB) CNN-IQ (98%) CNN-FFT (99%)	-	2019
Onboard Spectral Analysis for Low-Complexity IoT Devices [94]	ISA100.11a RF jamming IEEE 802.11n	Real data collected using TelosB nodes, WiFi AP and USRP radio based jammer	Spectrum reconstruction using center frequency, bandwidth and signal spectral shape	Channel blacklisting	PDR (Increased by over 50%)	-	2020
CQI-Based Interference Detection and Resource Allocation With QoS Provision in LTE-U Systems [95]	WiFi LTE-U	Simulation based work	K-means clustering using CQI and user location	Adaptive subcarrier and power control	Throughput (Increased)	-	2021
Coexistence Scheme for Uncoordinated LTE and WiFi Networks Using Experience Replay Based Q-Learning [96]	IEEE 802.11n LTE-U	Simulation using ns-3	Technology based recognition based on [93] WiFi load estimation as in [65]	Adaptive TXOP using traditional Q learning Adaptive TXOP using ER based Q learning Adaptive TXOP using RER based Q learning Adaptive TXOP using rule based scheme	Throughput (Increased) Fairness (Increased)	-	2021
Coexistence Analysis of D2D-Unlicensed and Wi-Fi Communications [97]	WiFi D2D-U	Simulation using Matlab	NA	Listen before talk Duty cycling	Throughput (Increased)	-	2021

Interference faced by WiFi is the studied in [101] initially using commercial WiFi TXM/RCVs in presence of various interferers. A file transferred using a smartphone Bluetooth acted as a low power interferer to WiFi. BL and WiFi at 1m separation reported a WiFi throughput reduction of less than 10 Mbps. However at greater separation, throughput reduction was found to be was minor. Amongst the high power interferers, the baby monitors and Cordless phones completely overwhelmed WiFi transmission and observed throughput was zero while MW Owens reduced the throughput by 35-90%. A modified WiFi receiver using USRP2 Radio and GNU was done to observe the effect of no Carrier Sense (CS) so as to determine if WiFi is refraining from transmission or packet collision. Results showed that the effect of interference is very high causing packet collisions and disconnectivity is faced even with no CS. Proposed Technology Independent Multi-Output (TIMO) uses 2×2 MIMO WiFi TXM/RCVs receiver. On detection of consecutive checksum failures, TIMO computes soft errors (difference in IQ constellation mapping of received signal with the nearest point). The rapid increase and decrease of soft errors indicates the interference duration for which channel estimation and decoding is initiated. Moreover in the absence of interferer, the MIMO design also supports for multiplexing hence increasing data transmission.

A plethora of multi-vendor sensing and automation devices operating in Industrial WSNs require stringent timing and reliable performance whilst sharing the same frequency domain and geographical area. An automated collaborative coexistence management (ACCM) based approach is proposed in [102] which utilizes a mediator node/CCP. Network manager nodes of each network share details (periodic data nodes, allowable delay and aperiodic data) to CCP. CCP devises a resource plan defining the Integrated Super frame Duration (ISD) comprising of three slots, one for each network so only one network is active in a slot and the appropriate scheduling of periodic and non-periodic data of each IWSN to ensure coexistence.

In [103], coexistence from the perspective of 6G (sixth generation) networks comprising of massive scale IoT networks is discussed. To fulfill the spectral and QoS requirements of 6G, the latest NR-U uses the shared spectrum for radio access. Such dense deployment and shared spectrum use would give rise to inter cell and intra cell interference. Consider a dense IoT scenario in which a massive number of 6G MNOs (mobile network operators) are coexisting with multiple WiFi APs. A Coordinated multi-point (CoMP) server is envisioned, that connects to all MNOs and performs synchronization and coordination. The subspace occupied by WiFi is estimated and a spatial LBT (listen before talk) is used to ensure the MNOs and WiFi transmissions are spatially separated. MNOs then engage in joint beam forming to maximize their throughput on a global level.

NR-U also includes for the use of 60 GHz millimeter wave (mmWave) unlicensed band that was previously considered unideal for transmission due to high losses. NR-U overcomes the shortcomings of mm wave signals by using antenna arrays and beamforming. In [104], a coexistence framework for WiGig (802.11ay) with mmWave NR-U has been proposed. The WiGig AP performs BFT (beam forming training) by sending beacon frames via different sectors. Each WiGig user perform SNR estimation to the AP and then trains its sectors by sending SSW (sector sweep) frames containing the best SID (sector identification) i.e. the identifier of the highest SNR WiFi AP. The AP acknowledges and the most optimal beam for the AP and the user is identified. User grouping occurs on the basis of best SID reported by the users. Hence inter-WiGig system interference is managed by semi orthogonal MIMO allocation. Beam refinement is done by analyzing WiGig user channel feedback and beam forming (BF) vector calculation. NR-U AP also studies the BF vector for interference channel estimation and performs scheduling and adaptive power control to keep interference caused by NR-U within limits.

In [105], Carrier Sense Adaptive Transmission (CSAT) has been used for time scheduling LTE and WiFi transmissions that would otherwise interfere with one another due to shared spectral occupancy. CSAT is a time division technique that splits time into frames. For x duration of the frame, LTE is enabled while WiFi is allocated to the remaining frame duration. To ensure fairness and throughput efficiency of both systems, a central control (CC) authority supervises the time scheduling by adaptively configuring airtimes as per traffic loads. The LTE and WiFi frame requests are modelled as an M/M/1 queue and optimal airtimes are found using Q-learning.

In [106], coexistence between WiFi and LTE is achieved using software defined network (SDN) controller and network function virtualization (NFV) based entities. All LTE-U BS report status to vNB (virtual LTE-U eNodeB) entity and the WiFi APs report status to vAC (WiFi access controller) entity. The NFV entities perform traffic load estimation of each technology using markov models and assigns the unlicensed bands to each technology as per traffic load.

Table 5 presents a summary of all the techniques discussed in this section.

C. ROUTING BASED MECHANISMS

These techniques involve routing solutions such as multipath routing protocols to route traffic around interference affected areas.

Geographical routing protocols utilize node location information to send packets to the hop which is geographically closest to the destination node. While these protocols are highly scalable, they require careful management of interference. Particularly in indoor environment, nodes will be blind to nearby walls, furniture and BL and WiFi interferers. Proposed routing algorithm in [108] uses node location as well as interference levels as the routing metric yielding promising improvements in presence of interferers.

Urban-X [109] proposes a coexistence aware framework for wireless mesh nodes facing interference from PNs

TABLE 5. Hardware based coping techniques.

Method	Signal Classes	Dataset	IDI Details	Coping Mechanisms	Performance	Overhead incurred	Year
A Centralized Cooperative SNMP-based Coexistence Management Approach for Industrial Wireless Systems [98]	Industrial WLAN BPSK interferer	Real simulations using SSU (Ettus USRP N210 and RFX2400), AP (Phoenix Contact FL WLAN 5100) and Clients (Siemens Scalance W784-1RR) BPSK interferer generated using VSG	NFSC	CCP based resource allocation	Resource Calculation time (1 ms)	CCP helper node required	2017
Resource Allocation for a Wireless Coexistence Management System Based on Reinforcement Learning [99]	Wireless Communication system and Interferers (WLAN Wireless HART)	Synthetic data generated using GNU radio	DNN	Spectral resource allocation based on DQN DDQN	98% prediction accuracy	CCP helper node required	2018
Coexistence Aware Clear Channel Assessment From theory to practice on an FPGA SDR platform [100]	WiFi WSN	Real data generated using a modified WiFi based on Wireless open-Access Research Platform (WARP) SDR and WSN nodes	NA	WSN aware WiFi CCA (Energy Detection based CCA and Matched Filter based CCA)	WSN good put (Increased)	Low latency hardware platform required	2013
Clearing the RF Smog: Making 802.11 Robust to Cross-Technology Interference [101]	WiFi MWO Analog baby monitor DSSS cordless phone	Real WiFi data generated using iperf with commercial WiFi module, USRP based WiFi and TIMO enabled USRP based WiFi in presence of real interferes	NA	Modified MIMO WiFi Receiver using a dual antenna USRP2 radios	14 times reduction in Packet Loss	MIMO receiver requirement	2011
Collaborative Coexistence Management Scheme for Industrial Wireless Sensor Networks [102]	Wireless HART ISA100.11a WIA-PA	Simulation done using OPNET and openZB [107]	NA	CCP based networks' scheduling	Real-time message delay remained under the allowable limits	CCP node required	2019
Joint Beamforming Coordination and User Selection for CoMP Enabled NR-U Networks [103]	6G NR-U WiFi	Simulation environment not specified	NA	CoMP server based spatial LBT and coordinated beamforming	System data rate (Increased)	CoMP node required	2021
Millimeter-Wave NR-U and WiGig Coexistence: Joint User Grouping, Beam Coordination and Power Control [104]	mmWave NR-U WiGig (IEEE 802.11ay)	Simulation environment not specified	NA	MIMO user grouping, coordinated beam forming and power control	Spectral efficiency (Increased) intra/inter-RAT interference (Reduced)	NR-U AP modification	2021
Coexistence of LTE-Unlicensed and WiFi: A Reinforcement Learning Framework [105]	LTE-U WiFi	Simulation environment not specified	NA	Markov decision and Q learning based CSAT time scheduling	-	Central control entity required	2021
A Delay Balanced Adaptive Channel Allocation Mechanism for LTE-U and WiFi Coexistence Systems [106]	LTE-U WiFi	Simulation done using MATLAB	NA	Markov model based load estimation and channel allocation	Access delay (Reduced) Fairness (Increased) Blocking probability (Reduced)	SDN controller with vNB and vNC	2021

(primary nodes) such as 802.11 access points (APs) as well as Bluetooth and ZigBee devices resulting in an interference aware Cognitive mesh networks (CMN). CMNs exchange channel allocations with all neighbors. Each CMN periodically measures workloads for all available channels, the channel with the highest capacity and which is the least utilized by a node's neighbors (to prevent inter system interference) is selected. A multipath routing algorithm is also used to route packets based on the varying paths condition.

Heterogeneous wireless networks create interference with respect to routing resulting in rapid network changes and nodes becoming isolated due to interference. Interference generation time and volume is dynamic hence HIADR (HI-Aware Dynamic Routing) protocol [110] takes the interference status of nodes into account and reroutes/scatters packets through nodes that are weakly/not affected. It is motivated from the theory of potential in classical physics. RSSI measurements in presence of no interference, WiFi and Microwave were done to find their respective thresholds which is then used as the HI (Heterogeneous Interference) value alongside other metrics. Results show an increase in PRR (Packet Reception Rate) and FPA (Forwarding Packets Amount). The routing protocol is resilient to interference but at the expense of increased APL (Average Path Length) because packets are rerouted around interfered links.

Routing in cognitive radio ad hoc network (CRAHNs) is complex due to CR's opportunistic transmission nature. The use of radio tomography i.e. creation of spectral map of an area using signal/interference measurements would give a visual clue about the spectral holes at a given time thus identifying potential routes. Proposed spectrum map empowered opportunistic routing (SMOR) [111] uses a quantized spectrum map for small scale CRAHNs containing the spectral occupancy state (0,1) of each block in spectrum map so that occupied blocks be avoided while routing. For large scale CRAHNs, a regular radio map is used where the exact interference levels at each point is known. By estimating the required minimum power to transmit without causing interference to PUs (Primary Users), high spectral efficiency is achieved.

Improved Urban-X for CMNs is a cross layer network architecture that intelligently adapts itself to the dynamic channel characteristics as proposed in [112]. It provides network adaptation on three levels i.e. frequency change, path/route change and load division. The architecture comprises of Mesh Clients (MCs) connected to Mesh Routers (MRs) that form a central backbone and provide connectivity to IMG (Internet Mesh Gateway). The network function virtualization (NFV) and SDN proves to be a much easier and effective implementation of Urban-X.

Interference Aware Heuristic Routing Protocol (IAHR) [113] is an energy conserving routing protocol to extend the lifetime of a WHAN (Wireless Home Automation Networks) which are subject to interference from WiFi, Bluetooth, smart meter, cordless phones, and microwave ovens. Sensor Nodes (SN) periodically send residual energy, location information and link information to neighbor SNs. Base Station (BS) that are full function devices broadcast their location to SNs. Multiple BSs are connected to a GS (Gateway Server). IAHR finds out the most optimal path between SNs and BS using local distance (the distance traversed to reach current node from source node), global distance (estimated Euclidean distance b/w SN and BS), Longevity factor/node energy and LQ (link quality) value i.e. a weighted value as per interference levels (below threshold (100), above high threshold 6 dB (0), otherwise (High thresh-SNR)).

In M2O (Many to One) source routing protocol, multi hop routing is done i.e. RREQ (Route Request) messages are sent and multiple routes to one destination nodes exist. Routes are ranked by a cost value that depends upon the successful transmission probability (ρ_z) which varies with time due to hidden node problem, external interferers etc. An optimized route selection procedure is proposed in Unicast Round Ribbon (U-RR) [92] by modifying the ZigBee link cost estimator for multi hop transmissions. The improved link cost calculator uses regular link state (LS) as well as unicast packets to calculate $\rho_{z.}$ Results show U-RR performs better than LQI (Link Quality Indicator) and LS based cost calculators.

In [114], Cognitive radio Adhoc networks (CRAHNs) and Primary Users (PUs) coexistence is discussed. CRAHNS are cognitive radio (CR) based networks that can assess their environment in real time and reconfigure their transmission parameters to optimize network performance. A PU is a licensed band user while the Secondary User (SU) is an unlicensed band user that can opportunistically transmit in the licensed band if PU stops its transmissions. A cross layer routing protocol is proposed i.e. the CRAHN nodes perform spectrum sensing to find idle channels and adjust their parameters accordingly. Moreover spectrum occupancy information is also considered in the routing process to avoid PUs.

In the coexisting WiFi and WSN networks in [115], the WSN network paths are divided into trees and different channels are used in different trees. On encountering interference, the channel within a tree is switched. If channel switching is inadequate, rerouting is done to avoid the interference.

A comparative analysis of the above techniques is summarized in Table 6.

D. CLUSTER HEAD BASED MECHANISMS

Cluster head (CH) based techniques modify the traditional CH by making it interference aware and manage interference on a cluster level.

In the CH based network of [117], a channel hopping based interference mitigation is proposed. On detection of packet errors exceeding a threshold, the CH performs energy detection and decides the presence of interference based on thresholds. It then alerts all cluster members to switch from ST (Single channel transmission) to MT (Multi-channel Transmission) via MT beacon. The nodes communicate with the CH using via a predetermined channel hopping sequence. The CH monitors the link conditions of all hopping channels

TABLE 6. Routing based coping techniques.

Method	Signal Classes	Dataset	Routing Metrics	Thresholds	Performance	Year
Interference-aware Geographical Routing for Sensor-nets in Indoor Environments [108]	WSN WLAN (802.11n/g)	Real data generated using MTM-CM3000 based WSN and N200UA WLAN adaptor	Link Quality(Receive power threshold) Distance to destination	-	PDR increased by 60% as compared to GPSR Energy consumption nearly halved as compared to GPSR	2009
Cognitive Multi-Radio Mesh Networks on ISM Bands: A Cross-Layer Architecture [109]	WiFi ZigBee BL	Synthetic data generated using ns-2	Channel having highest channel capacity and least reused by neighboring CMNs	-	Throughput increased(double than that of DCA)	2010
Avoiding Heterogeneous Interference through Dynamic Routing in Wireless Sensor Networks [110]	WSN Microwave Wi-Fi	Real dataset generated using MICA platform and real interferers	Min Depth/hop count MAX PE Min HI Intensity	no interference (-90 dB) Wi-Fi (-60 dB) microwave (-85 dB)	PRR (Packet Reception Rate) increased APL (Average Path Length) increased due to rerouting	2013
Spectrum Map Empowered Opportunistic Routing for Cognitive Radio Ad Hoc Networks [111]	CRAHN	Simulation	Spectral occupancy fading link service rate	-	End to end delay (Reduced)	2014
Toward network function virtualization for cognitive wireless mesh networks: a TCP case study [112]	WiFi PN interferer	Simulated in ns-2	Channel having highest channel capacity and least reused by neighboring CMNs	-	Throughput increased from previous implementations	2015
An Interference Aware Heuristic Routing Protocol for Wireless Home Automation Networks [113]	WHAN with interferers	Simulated in Omnet+	Local distance Global distance Longevity factor/node energy LQ value calculation	-	PDR(15% increased) Remaining Energy increased Network Lifetime (Available for more rounds) Routing Overhead(Less control packets required as interference is quantized beforehand instead in real-time) Average Packet Delay decreased	2016
Improving Route Selections in ZigBee Wireless Sensor Networks [116]	WSN WiFi	Simulated in ns-3	Modified link cost calculation using LS and Unicast packets	-	Retransmission under WiFi (Reduced by 20%)	2019
Spectrum-aware cross-layered routing protocol for cognitive radio adhoc networks [114]	CRAHN PUs	Simulated in ns-2	Channel capacity Number of PUs	-	Increased throughput Reduced end-to-end delay, channel switching, and interference to PU	2020
Joint Channel Allocation and Routing for ZigBee/Wi-Fi Coexistent Networks [115]	WSN WiFi	Simulation in QualNet 7.1	Channel switching Re-routing	-	Packet arrival ratio (Increased)	2021

using acknowledgment (ACKs) and eventually hand offs to the best channel i.e. in ST mode.

CRSN (Cognitive Radio Sensor Network) use CR as WSN nodes making the most optimal use of spectrum that is unused by PUs. Resulting network is an interference aware self-configuring network that provides good performance in comparison to highly congested ISM band. CogLeach [118] is the cognitive form of LEACH protocol. LEACH's CH

TABLE 7. Cluster head based coping techniques.

Method	Signal Classes	Dataset	Cluster Head Election	Intra Cluster Technique	Performance	Year
Interference Mitigation in IEEE 802.15.4 Networks [117]	WSN WiFi	Simulation environment not specified	Normal	Channel hopping in presence of interference only	Throughout increased Energy Consumption decreased	2011
CogLEACH: A Spectrum Aware Clustering Protocol for Cognitive Radio Sensor Networks [118]	CRSN (Cognitive Radio Sensor Network)	Simulation environment not specified	CH with the highest number of idle channels	TDMA and DSSS	Throughput increased	2014
Frequency hopping in IEEE802.15.4 to mitigate IEEE 802.11 interference and fading [119]	WSN WiFi	Real dataset collected using 6LoWPAN Sensinode Devkit , 802.11 NIC and Multi-Generator (MGEN) software	Normal	Channel hopping Non overlapping channel selection for FH	PDR increased by 38% (FH) PDR increased by 10% (FH and channel selection)	2018
Intelligent Cognitive Radio Ad-Hoc Network: Planning, Learning and Dynamic Configuration [120]	CRAHN PUs	Simulated using C++, MATLAB and Tensor Flow	Normal	SCF based PU/SU/Noise detection Q learning based network reconfigurations	Cluster lifetime increased by 30%	2021

election process is made spectrum aware by choosing vacant channel as the metric.

The effect of WiFi interference, Rayleigh and Rician fading are mitigated in [119] using FH (Frequency hopping). All cluster nodes communicate with CH using FH. A timing synchronization protocol is used to synchronize the CH with its cluster member after which the hopping pattern is exchanged and transmission occurs. Moreover, on the analysis of WSN and WiFi channels, four WSN channels (15, 20, 25, and 26) were found to not overlap with North America WiFi channels. On intelligent selection of hopping channels, a further 10% increase in PDR is achieved.

In [120], an improved cluster head based coexistence scheme is proposed for CRAHNs and PUs. The system comprises of member nodes (MNs) amongst which CH is selected and several gateway nodes (GNs) interconnect multiple CHs. Each CH asks MNs to perform spectrum sensing using SCF (spectral correlation function) based CNN to detect the presence of PU, SU or Noise. Since the PU system changes dynamically, the CHs adaptively reconfigure the network. All nodes perform spectrum sensing and channel quality assessment based on PU presence using Q-learning which is then shared with other nodes for the next CH election procedure.

A summary of cluster head based mitigation techniques is presented in Table 7.

VII. OPEN ISSUES

A variety of WII techniques and subsequent coping mechanisms have been proposed and validated to be providing optimized performance.

The implementation of interference detection or coexistence mechanism is subject to node hardware constraints. For instance, in the WSN COTS (commercial off the shelf) nodes in particular, the energy sampling is not as fine grained as compared to a sophisticated software defined radio (SDR) hence resulting in sub-nyquist sampling [57]. This results in envelope information loss and hampers the time and frequency resolution of the signal. State of the art interference detection techniques utilizing such spectrum information will perform optimally on spectrum analyzers or SDR based platforms, but their performance will be limited in WSN COTS devices due to simple radio front ends and processing unit. Hence there exists a requirement of ML models and techniques that can perfectly decode the dependencies extracted from the low resolution data supplied by low end network nodes.

Machine learning models to be used for interference detection or interference coping must take into account node memory. Trained deep learning models often require more memory and would require node modification. A healthy compromise between model complexity, accuracy and memory constraints need to be made. There exist potential in exploring traditional pattern recognition algorithms alongside deep learning algorithms to obtain the benefit of simpler yet effective models.

Robust models with simpler data representations are desired. Recent advances in Computer Vision have motivated the use of spectrograms making WII an image classification task. This data transformation yields unique observable features that are otherwise concealed in raw data and offer good classification accuracies. Since most works use normal spectrograms, there exist a potential in analyzing other time-frequency analysis methods and transforms. Since FFT and other frequency transforms require dedicated hardware and are often incompatible with ordinary WSN nodes, there exist the possibility of pushing these resource hungry sensing into several sophisticated nodes instead of all network nodes. The data gathering, sensing and coordination in such a hierarchal architecture is to be explored further.

VIII. CONCLUSION

With the upcoming wireless communication trends, there is an ever growing importance of the unlicensed bands. Moreover ISM bands will also be used by traditional licensed band users (LTE) for traffic offloading purposes. Coexistence management amongst all these heterogeneous technologies is of paramount importance to ensure fairness and meet the QoS requirements of all ISM users.

This survey gives an overview and comparison of the main technologies that predominantly utilize and rely on ISM bands. Moreover a step by step approach to Coexistence Management is also discussed. Firstly in this paper a comprehensive survey of wireless interference identification techniques is presented. Wireless Interference Identification (WII) is important in order to recognize explicitly which technology enabled devices are interfering with the ongoing transmissions in order to implement technology specific coping mechanisms. WII can also be applied to spectrum monitoring to monitor occupancy on large scale. Furthermore in this paper analysis of RSSI/IQ based WII techniques that use raw radio samples for detection and can be realized on most COTS hardware is also presented. Also spectral based techniques are discussed owing to a new paradigm of making WII an image classification task. Spectral analysis techniques require higher processing power and special nodes, however they offer an interesting and visual way of WII.

Also a comprehensive survey of proposed coexistence techniques is also presented in the paper. These techniques are categorized on the basis of software based techniques that require protocol stack modification and hardware based techniques that require additional helper nodes/ special antennas to achieve coexistence. In the end, the paper discussed interference management via interference aware routing and improved clustering mechanism techniques.

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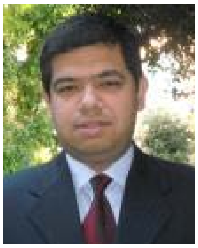

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