UNIVERSITI PUTRA MALAYSIA

A REINFORCEMENT LEARNING-BASED ENERGY -EFFICIENT SPECTRUM-AWARE CLUSTERING ALGORITHM FOR COGNITIVE RADIO WIRELESS SENSOR NETWORK

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By

IBRAHIM MUSTAPHA

Thesis Submitted to the School of Graduate Studies, Universiti Putra Malaysia, in Fulfilment of the Requirements for the Degree of Doctor of Philosophy

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DEDICATIONS

To my parents . . . .

Abstract of thesis presented to the Senate of Universiti Putra Malaysia in fulfilment of the requirement for the Degree of Doctor of Philosophy

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February 2016

Chair : Prof. Borhanuddin Mohd. Ali, PhD
Faculty : Engineering

Energy efficiency and spectrum efficiency are two main challenges in the realization of Cognitive Radio-Wireless Sensor Network (CR-WSN). Clustering is a well-known technique that could be used to achieve energy efficient communication and to enhance dynamic channel access in cognitive radio through cooperative sensing. While the energy efficiency issue has been well investigated in conventional wireless sensor networks, the latter has not been extensively explored. In this thesis, a Reinforcement Learning (RL) based clustering algorithm is proposed to address energy and Primary Users (PUs) detection challenges in CR-WSN. The scheme minimizes network energy consumption, improves channel utilization and enhances PUs detection performance from three different perspectives. Firstly, a RL based spectrum-aware clustering scheme in which a cluster member node learns energy and cooperative sensing costs for neighbouring clusters through exploration and imposes pairwise constraint to select optimal cluster. The optimal cluster minimizes network energy consumption and enhances channel sensing performance. Secondly, a weighted hard combining scheme that combines features of both quantized and hard combining schemes to minimize energy cost for reporting sensing result and improve PU detection performance. Thirdly, a RL based cooperative channel sensing scheme where a clusterhead learns channels dynamic behaviours in terms of channel availability, channel sensing energy cost and channel impairment to achieve optimal sensing sequence and optimal set of channels. Simulation results show convergence, learning and adaptability of the RL based algorithms to dynamic environment toward achieving the optimal solutions. Performance comparisons of the RL based clustering scheme with Groupwise spectrum-aware clustering scheme show that an energy savings of 9% and PU detection performance improvement of 11.6% can be achieved. Similarly, the results indicate that the proposed fusion scheme minimizes reporting energy cost by 70% and improves detection performance by 5.6\% compared to the quantized 3-bits scheme. Furthermore, the results show that with the RL based channel sensing scheme, a sensing energy cost savings of 15.14% per channel sensing cycle can be achieved while improving PU detection accuracy and channel utilization compared to the Greedy search approach. The overall result indicates viability and improved performance from the RL based scheme over the other bench mark schemes in terms of energy efficiency and PU detection performance which are vital to resource constraint devices.

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia sebagai memenuhi keperluan untuk Ijazah Doktor Falsafah

ALGORITMA PENGELOMPOKAN CEKAP TENAGA SPEKTRUM-SEDAR BENDASARKAN-PEMBELAJARAN PENGUKUHAN UNTUK RADIO-KOGNITIF RANGKAIAN SENSOR TANPA WAYAR

Oleh

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Februari 2016

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Kecekapan tenaga dan kecekapan spektrum adalah merupakan dua cabaran utama dalam merealisasikan Radio-Kognitif Rangkaian Sensor Tanpa Wayar(RR-STW). Pengelompokan adalah teknik terkenal yang memberangsangkan yang boleh digunakan untuk mencapai komunikasi yang cekap tenaga dan untuk meningkatkan akses saluran dinamik dalam radio kognitif melalui penderiaan kerjasama.Walaupun persoalan kecekapan tenaga telah dikaji dalam rangkaian sensor tanpa wayar konvensional,kecekapan spektrum belum diterokai secara meluas. Dalam tesis ini, algoritma pengelompokan berdasarkan Pembelajaran Pengukuhan(PP) dicadangkan bagi menangani cabaran pengesanan tenaga dan Pengguna Utama(PU) dalam RR-STW.Skim ini dapat mengurangkan penggunaan tenaga dalam rangkaian seterusnya dapat meningkatkan penggunaan saluran dan meningkatkan prestasi pengesanan PU-PU dari tiga perspektif yang berbeza. Pertama, PP yang berasaskan skim kelompok spektrum-sedar di mana nod ahli kelompok belajar tentang tenaga dan kos pengesanan kerjasama untuk kelompok jiran melalui penerokaan dan mengenakan kekangan dari segi pasangan untuk memilih kelompok yang optimum. Kelompok optimum dapat mengurangkan penggunaan tenaga rangkaian dan meningkatkan prestasi pengesanan saluran.Yang kedua, skim yang berwajaran keras yang menggabungkan kedua-dua ciri terkuantum dan skim penggabungan keras bagi mengurangkan kos tenaga bagi melapala untuk melaporkan hasil penderiaan dan meningkatkan prestasi pengesanan PU. Ketiga,PP berasaskan skim pengesanan saluran kerjasama di mana ketna kelompok belajar tingkah laku saluran yang dinamik dari segi ketersediaan saluran, kos tenaga penderiaan saluran dan kemerosotan saluran untuk mencapai urutan pengesanan yang optimum dan set saluran-saluran yang optimum. Keputusan-keputusan simulasi menunjukkan penu-mpuan, pembelajaran dan keupayaan menyesuaikan diri daripada algoritma PP berdasarkan kepada persekitaran yang dinamik ke arah mencapai penyelesaian yang optimum. Perbandingan prestasi skema pengelompokan berdasarkan RL dengan Groupwise spektrum-sedar Skema pengelompokan dapat mencapai penjimatan tenaga sebanyak 9% dan peningkatan prestasi pengesanan PU sebanyak 11.6%. Demikian juga, hasil kajian menunjukkan bahawa skema gabungan yang dicadangkan dapat meminimumkan kos tenaga pelaporan sebanyak 70% dan meningkatkan prestasi pengesanan sebanyak 5.6% jika dibandingkan dengan skema 3-bit terkuantum. Tambahan pula, keputusan menunjukkan bahawa dengan skema RL

berasaskan saluran pengesanan, penjimatan kos tenaga pengesanan 15.14% bagi setiap pengesanan saluran kitaran boleh dicapai seterusnya dapat memperbaiki ketepatan pengesanan PU dan penggunaan saluran berbanding dengan pendekatan carian Greedy. Secara keseluruhan hasil kajian menunjukkan bahawa kelayakan dan peningkatan prestasi dari skema berdasarkan RL berbanding skema penanda aras lain dalam hal kecekapan tenaga dan prestasi pengesanan PU yang amat penting kepada sumber peranti kekangan.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

ADC	Analogue to Digital Converter
AWGN	Adaptive White Gaussian Noise
BPF	Band-Pass Filter
BPSK	Binary Phase Shift Keying
BS	Base Station
CCSS	Centralized Cooperative Spectrum Sensing
CH	Clusterhead
CR	Cognitive Radio
CR-WSN	Cognitive Radio-Wireless Sensor Network
CSS	Cooperative Spectrum Sensing
DCSS	Distributed Cooperative Spectrum Sensing
DGWSA	Distributed Groupwise Spectrum Aware
DoF	Degree of Freedom
DSA	Dynamic Spectrum Access
EESA-RL	Energy Efficient Spectrum-Aware Reinforcement Learning Based
FC	Fusion Centre
FCC	Federal Communications Commission
GWSA	Groupwise Spectrum-Aware
IoT	Internet of Things
ISM	Industrial Scientific and Medical
M2M	Machine-to-Machine
MCMC	Malaysian Communications and Multimedia Commission
MDP	Markov Decision Process
MN	Member Node
MRC	Maximum Ratio Combining
PU	Primary User
RCSS	Relay Assisted Cooperative Spectrum Sensing
RF	Radio Frequency
RL	Reinforcement Learning
RL-NCCS	Reinforcement Learning Based Narrowband Cooperative Channel Sensing
SARSA	State-Action-Reward-State-Action
SLC	Square Law Combining
SLS	Square Law Selection
SNR	Signal-to-Noise Ratio
SSE	Sum of Square Error
SU	Secondary User
TD	Temporal Differences
TV	Television
TVWS	TV White Spaces
UHF	Ultra High Frequency
U-NII	Unlicensed-National Information Infrastructure
UWB	Ultra Wide Band
VHF	Very High Frequency
WHC	Weighted Hard Combining

WMAN	Wireless Metropolitan Area Network
WoT	Web of Things
WPAN	Wireless Personal Area Network
WSN	Wireless Sensor Networks

LIST OF SYMBOLS

$\mathcal{A}$	Set of actions
A_c	Average area of a cluster
A^*_{ex}	Optimal set of channels
a_k	Action selected in stage k
A_{pkt}	Advertisement packet
A^2_{sp}	Average spans for a cluster
Av^e_{k+1}	Channel availability
a_v	Number of available control channels
$\bar{b}_1$	Birth rate (OFF to ON) of PU activity
$\bar{b}_0$	Death rate (ON to OFF) of PU activity
B_{ap}	Aggregated processing data bits size
B_{pk}	Aggregated data bits size
B_{ss}	Event sensing data bits size
C_{av}	Average number of capacitance switching per cycle
C^c_{tr}	c_{th} Control channel
CD^e_j	Set of cooperative decisions of clusterhead j in episode e
CD^z_j	Cooperative decision of clusterhead j on z_{th} channel
CH_{j}	j_{th}-Clusterhead
CK	Set of available common licensed channels
cl_{j}	j_{th}-Cluster
$d_{i,j}$	Euclidian distance between member node i and clusterhead j
$d_{j,g}$	Euclidian distance between clusterhead CH_j and its neighbouring clusterhead CH_g
D^e_{k+1}	Local decision accuracy
E_{am}	Energy dissipation for amplifying signal
E_{bd}	Energy dissipation for broadcasting cooperative decision
E_{cs}	Energy dissipation for sensing channels
E^{cs}_{MN}	Energy consumed by a member node
E^{cs}_{CH}	Energy consumed by a clusterhead
E^{cs}_{total}	Total energy cost for cooperative channel sensing
E_{dp}	Energy dissipation for processing data
E^{dt}_{total}	Total energy dissipation for data communications
E_{ec}	Energy dissipation for running radio electronics
$E^e_{dcost,j}$	Energy cost of j_{th}-cluster in episode e
$E^e_{pcost,j}$	Cooperative cost of j_{th}-cluster in episode e
$\mathrm{E}^{\mathrm{Re}}_i$	Residual energy of SU i
E_{Intr}	Energy dissipation for intra cluster data communication
E_{int}	Energy dissipation for inter cluster data communication
E_{log}	Energy dissipation for data logging
E_{mp}	Energy dissipation for amplifying signal
E_{net}	Network energy consumption
E_{ps}	Number of episodes
E_{rH}	Energy dissipation for receiving aggregated data packets
E_{rM}	Energy dissipation for receiving data from member node
E_{rp}	Energy dissipation for reporting local decision
E_{rx}	Energy dissipation for receiving local decision

E_{TC}^{set}	Set of energy consumed for data transmission
E_{sp}	Energy dissipation for processing received signal
E_{sr}	Energy dissipation for operating the electronic circuit
E_{sp}	Energy dissipation for processing the signal
E_{ss}	Energy dissipation for event sensing
E_{tH}	Energy dissipation for transmitting aggregated data packets
E_{tM}	Energy dissipation for transmitting data to clusterhead
f	Micro-controller Operating frequency
f_s	Sampling frequency
g_n	Number of regions
H_o	Null hypothesis that indicates absence of PU
H_1	Hypothesis that indicates presence of PU
H_n	Set of neighbouring clusterheads
H_s	Set of clusterheads
H_j^v	Set of vacant channels detected by j_{th} clusterhead
I_o	Leakage current
$I_x(a)$	x_{th}-order modified Bessel function of the first kind.
k	Stage index of the process
k_q	Number of clusters
k_q^*	Optimal number of clusters
L	Length of network
LD_i^e	Set of local decisions of i_{th}-SU in episode e
LD_i^z	Local decision of i_{th}-SU on z_{th} channel
$\mathcal{M}$	Number of PUs
M_i^v	Set of vacant channels detected by i_{th} member node
N	Number of cognitive radio sensor nodes
$\mathrm{N_A}$	Area of network
N_{cy}	Number of clock cycle per task
$\mathrm{n_g}$	Number of neighbouring SUs
n_{hg}	Number of neighbouring clusters
n_{hv}	Number of vacant channels detected by a clusterhead
n_{mv}	Number of vacant channels detected by a member node
N_o	Number of signal sample
n_p	Constant parameter for microprocessor
n_{sl}	Minimum number of mini slots per reporting slot in control channel
n_z	Number of licensed channels
p	Softmax action selection probability
P_{am}	Power consumed by power amplifier
P_{bc}	Probability that channel is correctly sensed as occupied
P_{bf}	Probability that the channel is falsely sensed as occupied
P_{bs}	Probability that the channel is busy
P_d	Probability of detection
P_{dc}	DC input power
P_{ed}	Power consumed by energy detector's circuit
P_f	Probability of false alarm
P_{ic}	Probability that the channel is correctly sensed as vacant
P_{if}	Transition Probability

P_{oc}	Probability that the sensed channel is occupied
P_{rd}	Power consumption for reading a packet from memory
P_{rx}	Power received at the receiver
P_{ss}	Power consumption for event sensing
P_{tx}	Transmission power
P_{vc}	Probability that the sensed channel is vacant
P_{wr}	Power consumption for writing a packet into the memory.
$P^{e}_{w,k+1}$	Pairwise constraint condition
$Q_{d,j}$	Cooperative probability of detection
$Q_{f,j}$	Cooperative probability of false alarm
Q^{e}_{k}	State-action value for choosing action a in state s
$\mathbb{Q}(a,x)$	Generalized Marcum Q-function
$\mathcal{R}$	State reward function
r_{k+1}	Immediate reward in stage k
R_{max}	Maximum transmission range
rw_{ak+1}	Reward attributed to channel availability
$rw^{e}_{C,k+1}$	Reward attributed to cooperative cost
rw_{ek+1}	Reward attributed to energy consumed for channel sensing
$rw^{e}_{E,k+1}$	Reward attributed to energy cost
rw_{lk+1}	Reward attributed to local decision
$R^{e}_{wt,k+1}$	Weighted average reward
$\mathcal{S}$	Set of states
S_k	State in stage k
S^{*}_{eq}	Optimal channel sensing sequence
S^{e}_{ch}	Set of licensed channels in episode e
T	Observation interval
$\mathcal{T}$	State transition function
t_b	Average busy time of the channel
T_{cs}	Channel sensing duration
t_{id}	Average idle time of channel
T_{rpt}	Total duration for result reporting
T_{ss}	Event sensing duration
V_s	Source voltage
V_t	Terminal voltage
$\hat{w}_{\overline{m}}$	Weight contribution of $\overline{m}_{th}$ reward
$x(t)$	Zero-mean additive white Gaussian noise
Y	Test Statistic
y_i	Observed signal energy of i_{th} SU
$z(t)$	Channel gain between PU and SU
λ	Detection threshold
λ_a	Threshold for a_{th} region
$\Gamma(\text{a}, \text{x})$	Upper incomplete gamma function
$\Gamma(\text{x})$	Gamma function
ψ_i	Percentage of clusterheads
φ_n	Number of vacant channels detected by SU n
χ^2_a	Central chi-square distribution with a DoF
$\chi^2_a(b)$	Non-central chi-square distribution with a DoF, and non-central parameter b

γ	Discount factor
γ_s	Signal-to-noise ratio
τ^{cs}	Channel sensing slot
τ^{dt}	Data transmission slot
τ^{rp}	Reporting slot
τ_{av}	Average sensing time for each channel
τ^{e}	Temperature of Softmax action strategy in episode e
ρ	Nodes distribution density in a cluster
μ	Time bandwidth product
π^*	Optimal policy
α	Learning rate
ϑ	Constant parameter for antennas characteristic
η	Drain efficiency
ω	Constant parameter for radio environment
β	Free space path loss exponent

CHAPTER 1

INTRODUCTION

1.1 Background

Tremendous growth in microelectronics technology and wireless communication applications have led to the widespread use of Wireless Sensor Networks (WSNs) in a wide variety of applications areas ranging from agriculture to military, environmental, commercial, scientific, healthcare and industry. In addition, WSN was envisioned to be the main enabling component in driving revolutionary technologies such as Internet of Things (IoT), Machine-to-Machine (M2M) and Web of Things (WoT) into reality [1]. Many objects and electronics devices are seamlessly and efficiently sense, collect and share data across the network for various applications.

Wireless sensor node is a self-organizing *ad hoc* entity equipped with communication, sensing and computing module that enables it to monitor certain events such as temperature, humidity, images, motion and seismic related signals in a geographical area and report the information to a sink node for further processing. Generally, WSN consists of huge number of nodes that are either systematically or randomly dispersed in a specific area to accomplish a particular application requirement. The main task of a sensor node is to sense, process and transmit data to neighbouring nodes or sink nodes. The sink node collects sensing data from sensor nodes and sends it to a gateway that interconnects different networks. Wireless sensor nodes are characterized by constrained memory, power, and computational resources.

Proliferation of wireless sensor nodes and other wireless devices based on Bluetooth, Wi-Fi and ZigBee technologies have led to severe congestion in the usable unlicensed Industrial Scientific and Medical (ISM) spectrum band and hence pose operational challenges to the wireless devices [2]. Federal Communications Commission (FCC) report [3] revealed that many spectrum bands that are assigned to licensed users (primary users) for various wireless communication services are underutilized. Similarly, studies on spectrum bands usage carried out in many countries including Malaysia [4], Spain [5], Singapore [6], Germany[7], New Zeeland [8] , UK [9] and USA [10] at different locations show that large portion of licensed radio spectrum bands have not been efficiently utilized most of the time. The utilization of licensed radio spectrum bands varies from 15% to 85% of the spectrum which indicates significant disparities in the usage of the radio spectrum bands [11]. Transition from analogue TV to digital TV transmission creates more spectrum opportunity for TV white space access and regulatory agencies of many countries had begun to explore this opportunity to address spectrum scarcity. Furthermore, there are more than 70 available channels in the VHF/UHF spectrum band that can be opportunistically accessed by secondary user and some hardware manufacturer such as Raytheon Corporation have recently developed cognitive radio hardware that can sense more than 10 TV channels simultaneously in a few seconds [12]. Generally, radio spectrum bands are divided into fixed number of different frequency channels in which segments of the radio spectrum bands are allocated for different wireless communication services as shown in Figure 1.1.

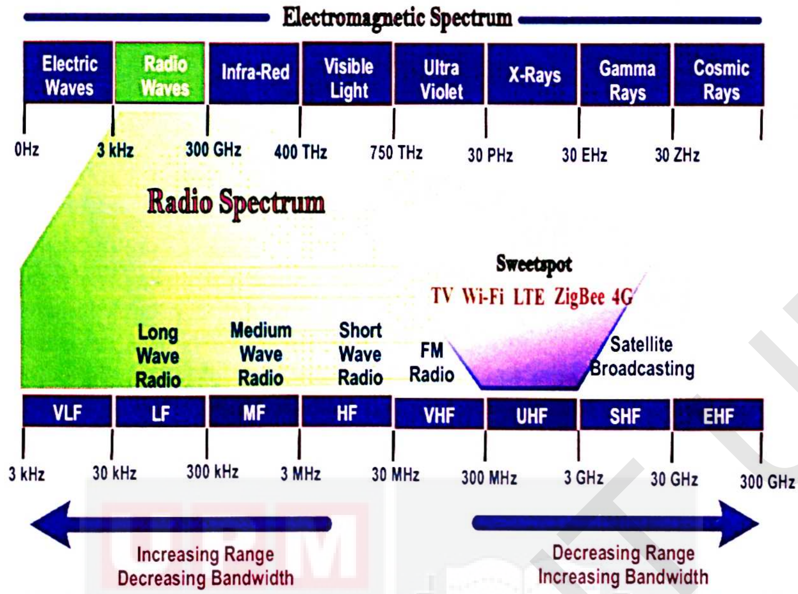

Figure 1.1: Schematic representation of radio spectrum bands and radio ranges [13].

Conventional policy of allocating spectrum bands to licensed users regardless of temporal and geographical variations has inadvertently contributed to the spectrum scarcity and hence necessitates the need for a paradigm shift from the static inefficient spectrum allocation policy to intelligent and dynamic spectrum access management. Static spectrum allocation policy can be explained analogically as allocating dedicated road lanes to some users (licensed users) and denying access to other users (unlicensed users) even though the allocated lanes are free of traffic for a long period while the unallocated lanes are congested as shown in Figure 1.2 [14].

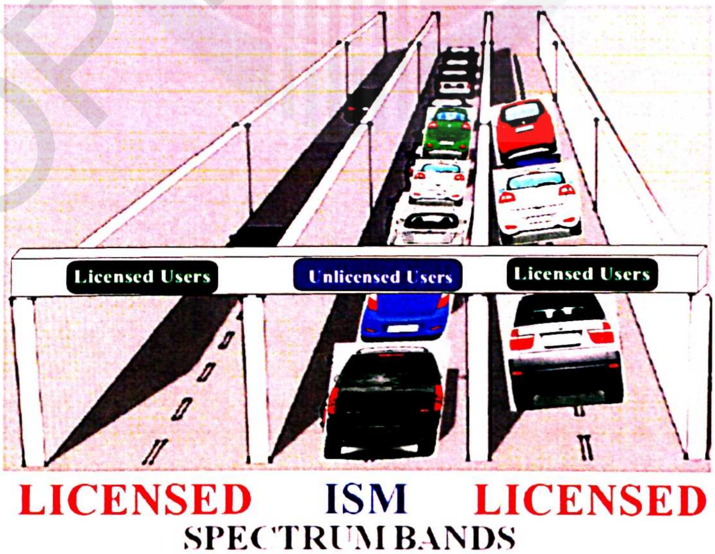

Figure 1.2: Analogy for static spectrum allocation policy [14].

To address this inefficient spectrum access, the FCC has recently released rulings [3] that allow unlicensed user to opportunistically access the unused portions of spectrum bands, also called white spaces. The guidelines permit Secondary Users (SUs) to transmit on TV white spaces frequencies (512 MHz-698 MHz)[15] without interfering with the incumbents TV transmitters and wireless microphones transmissions. To ensure maximum protection of the incumbent license users, the FCC proposed combination of local spectrum sensing and the use of geo-location database of primary users for the detection of TV White Spaces (TVWS) availability.

The spectrum sensing involves sampling the received signals and comparing it with a threshold to determine the availability of spectrum holes. On the other hand, the database is a repository of primary user signal strength at a given location and time based on propagation prediction model. While spectrum sensing to detect the presence of wireless microphone receivers or TV receivers at very low threshold of -114dB is challenging, geo-location database of primary user signal strength is unreliable for primary user protection because of the inability of the propagation model to predict coverage area of TV broadcasting and to estimate transmission power of licensed mobile user [15]. This motivates the need for spectrum sensing techniques that can accurately detect incumbent primary users. This research focuses on the spectrum sensing aspect.

Cognitive Radio (CR) has emerged as the viable technology for efficient utilization of spectrum holes or TV whitespaces by dynamically allocating the unoccupied licensed spectrum bands to unlicensed users in an agile manner without causing harmful interference to the Primary Users' (PUs) transmission as illustrated in Figure 1.3 [16] . Such a dynamic spectrum access provides not only the potential benefits of efficient spectrum utilization, but also reduces power used for transmission and reception by accessing lower frequency bands spectrum that have better operating parameters in terms of network performance and resource utilization [17]. Therefore, opportunist access of temporal and spatial spectrum holes is the main motivation for CR [18]. Note that, the terms CR node and SUs refer to the same thing and may be used interchangeable.

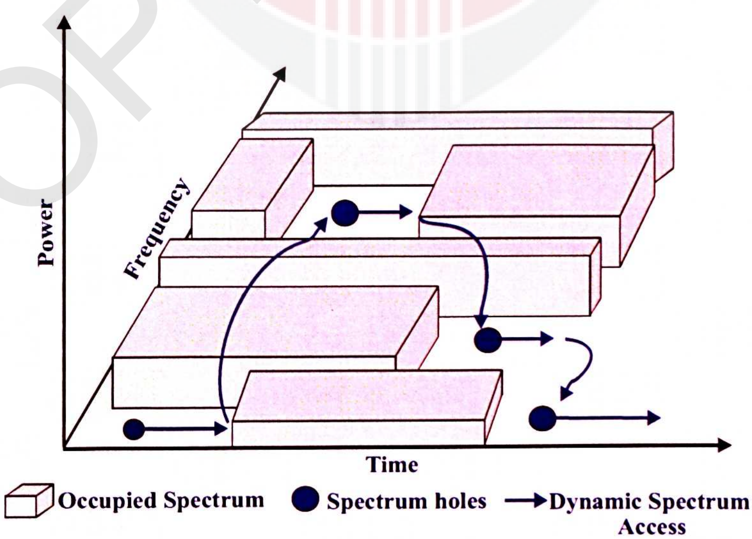

Figure 1.3: Spectrum holes and dynamic spectrum access [16].

Spectrum sensing is the main fundamental function of CR to detect the presence or absence of PUs in a licensed spectrum band. Its main goal is to identify and access spectrum holes without compromising PUs' transmission. In autonomous spectrum sensing, individual SU locally senses the spectrum bands and decides on the presence or absence of PU in the spectrum bands. However, this method is usually prone to channel impairments such as fading, shadowing, receiver uncertainty and multi-path interference which result from obstacles in close proximity or signal blockage [19].

Cooperative spectrum sensing has been identified in [20],[21] as a feasible method to tackle the aforementioned issues through exploration of multi-user sensing diversity to improve spectrum sensing performance. In this method, multiple SUs share their local sensing results and decide on the presence or absence of PUs in the spectrum band of interest. A Fusion Centre (FC) which could either be selected SUs or a dedicated entity performs decision fusion on the local sensing results obtained from individual SU and makes global decision about the availability of spectrum holes. Despite of the fact that the method achieved remarkable success in improving spectrum sensing performance, it also incurs heavy communications overhead, increases computational complexity, and decision making delay especially in large scale networks such as CR-WSN. Therefore, logical grouping of multiple SUs to form clusters and assigning a dedicated entity within the clusters to coordinate the sensing and data communication could mitigate these problems and also minimize network energy consumption. Generally, reliability of spectrum sensing is measured based on two performance metrics namely, probability of detection P_d and probability of false alarm P_f.

The need to properly harness the potentials benefits of cognitive radio technology in WSN to improve spectrum utilization and support many applications that involve monitoring of sensitive and critical activities in an environment led to emergence of Cognitive Radio Wireless Sensor Network (CR-WSN) [22],[23]. A CR-WSN is defined as the dispersed network of cognitive radio sensor nodes equipped with cognitive radio capability that dynamically utilize unused available spectrum bands to communicate sensed readings in either a single-hop or a multi-hop fashion to satisfy application requirement [22]. Integrating opportunist spectrum access capability to the sensor nodes enables them to adjust their transmission parameters to efficiently access the unused spectrum bands and enhance communication quality. This emerging technology is expected to be the most promising technology that has the potentials to address spectrum access challenges in conventional WSNs. However, practical realization of this breakthrough poses many challenges due to the resource constraints of the sensor nodes. Therefore, to address some of these challenges, legacy algorithms and techniques for WSNs need to be enhanced to improve network performance in terms of spectrum utilization and energy efficiency.

1.2 Problem Statements and Motivation

In general the main motivation for cognitive radio sensor networks is to effectively harness the potentials benefits of cognitive radio technology in WSN to improve spectrum access and utilization. Therefore, CR-WSN can be broadly used to support many applications that involve monitoring sensitive and critical activities in an environment. It offers several potential benefits and can be used in a wide range of application areas such as agriculture monitoring, home automation, industrial process control, military battlefield surveillance, health care monitoring, automotive control and civil infrastructure monitoring.

Generally, CR sensor nodes inherent resource constraint of conventional wireless sensor nodes consequently are characterized by limited energy, constraint storage and processing resources. They are normally powered by battery and usually deploy in inaccessible terrain which make it difficult or impossible to replace and/or replenish the batteries [24]. Although, cognitive radio sensor nodes can dynamically access multiple unused licensed channels for data transmission in order to address spectrum access and utilization challenges in conventional WSN [25], the additional task of opportunistic access to unused licensed channels through spectrum sensing incurs significant energy cost which drains more energy from the battery of the sensor nodes and hence shorten the life time of the network.This means CR-WSN inevitably consumes much large energy than conventional WSN due to the cognitive capability.

Therefore, energy-efficient spectrum access and communication to extend the lifetime of the network became major issues in CR-WSN. Existing schemes for energy-efficient data communication and spectrum access are mainly focused on conventional wireless sensor networks [26] and *ad hoc* cognitive radio networks [27] respectively, but the union of the two i.e CR-WSN has not been extensively explored. This necessitates the need for a framework that improves network performance in terms of energy efficiency, dynamic spectrum access and utilization. Thus, the main challenges in CR-WSNs are energy efficient communication to extend the lifetime of the network and PU protection from unlawful interference as illustrated in Figure 1.4.

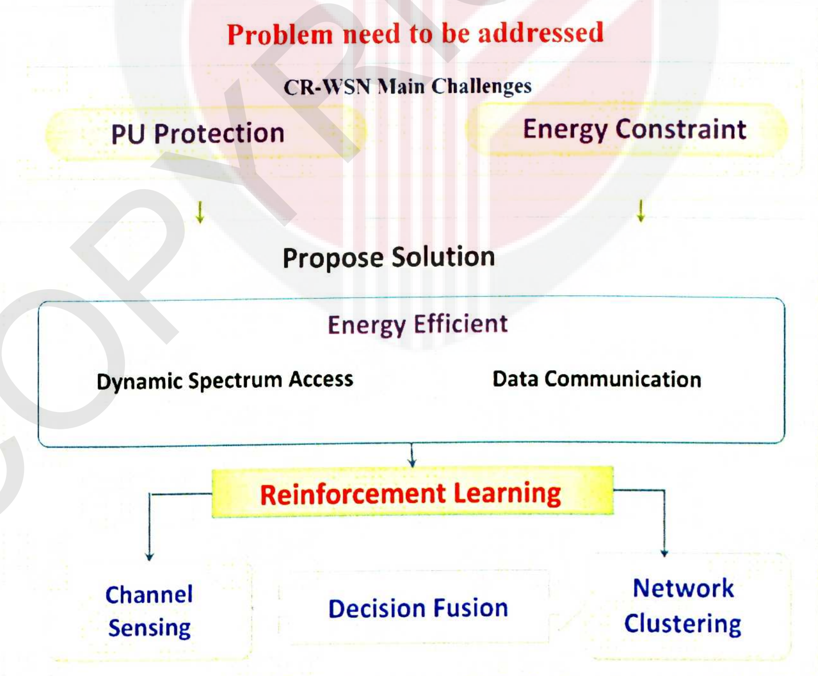

Figure 1.4: Illustration of the main challenges in CR-WSN and the propose solution.

Therefore, the main challenges can be formulated as energy minimization problem to optimize network energy cost for cooperative channel sensing and data communication while improving spectrum sensing performance.

A reinforcement learning based clustering and channel sensing schemes as well as decision fusion scheme are proposed to address these challenges. The main motivation for the reinforcement learning technique in cooperative sensing and network clustering is due to its ability to learn optimal behaviour in challenging or uncertain environments such as dynamic spectrum access. The technique is based on an agent that interacts with an environment by selecting an action that is likely to be beneficial and then receives a feedback from the environment in form of reward to optimise it behaviour. It allows agent to learn optimal channels and optimal cluster from interaction with the dynamic environment and adapt to unknown dynamic system to achieve optimal policy without model of the environment. Unlike heuristic search and dynamic programming techniques, the reinforcement learning technique eliminates the need of specifying an optimal action for each possible state a priori and also can cope with uncertainty about outcome of the action taken since goals can be specified in terms of reward measures, and with changing situations.

1.3 Aim and Objectives

The aim of this thesis is to propose RL based spectrum-aware clustering algorithm that can enhance spectrum sensing performance and optimise network energy consumption thereby extending the lifetime of cognitive radio sensor networks. Thus, the objectives of this thesis are to:

i. Minimize intra-cluster and inter-cluster communications energy cost and determine optimal number of clusters for the network.

ii. Optimize spectrum sensing energy cost and enhance performance of energy detection technique in terms of primary user detection.

iii. Optimized channels to be sensed so that network energy cost is minimized while improving spectrum sensing performance and utilization.

1.4 Scope of the Research

Cognitive radio is a vast area that encompasses multidisciplinary technologies that involves several research fields such as signal processing, information theory, dynamic spectrum access, communication protocols, and cognitive radio network architecture. However the main focus of this research is on developing energy efficient reinforcement learning based framework for cooperative channel sensing in a clustered cognitive radio sensor network. Therefore, the research is confine to addressing energy and primary user detection issues in cognitive radio sensor network using reinforcement learning technique. While there are many signal detection techniques, the framework basis on energy detection technique due to computation, memory and energy constraints of the cognitive radio sensor node. Therefore, the research complements the efforts made toward realization of cognitive radio technology application in WSNs.

1.5 Research Methodology

The research focuses on minimizing network energy consumption for cooperative spectrum sensing while improving spectrum sensing performance using Reinforce Learning (RL) approach as illustrated using a block diagram in Figure 1.5. The network is partitioned into logical groups of sensor nodes that form clusters, such that each cluster comprises of several sensor nodes called cluster member nodes and a clusterhead that coordinates the cooperative channel sensing and data communications.

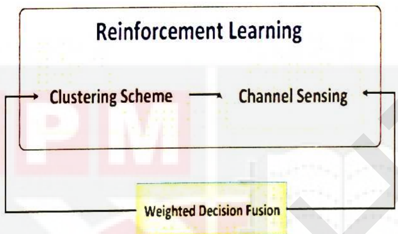

Figure 1.5: Illustration of the research methodology.

A RL based framework is proposed to minimize network energy consumption and enhance channels sensing performance as well as utilization. The framework is mainly comprises of three schemes aim at addressing the main fundamental challenges of cognitive radio sensor networks viz network energy consumption and PUs detection as illustrated in Figure 1.6.

Firstly, an Energy Efficient Spectrum-Aware RL based Clustering (EESA-RLC) algorithm that allows a member node to learn the energy and the cooperative sensing costs for neighboring clusters through exploration technique and selects an optimal cluster that satisfies pairwise constraints. The pairwise constraints guarantee that only nodes that have at least one common vacant channel with the clusterhead can form a cluster. The scheme allows each member node to learn and adapt to dynamic environment to select an optimal cluster that minimizes energy cost for intra and inter clusters data communications and to enhance spectrum sensing performance.

Secondly, a weighted hard combine decision fusion scheme that combines features of quantized and hard combining decision fusions schemes to balance trade-off between detection performance and communication overhead and also minimizes energy cost for reporting decision.

Thirdly, an Energy Efficient RL based Narrowband Cooperative Channel Sensing (EERL-NCCS) scheme in which a clusterhead learns channels' dynamic behaviors in terms of channel availability, channel sensing energy cost and channel impairment to achieve optimal sensing sequence and optimal set of channels. The optimal set of channels and optimal channels sensing sequence obtained through reinforcement learning minimize channel sensing energy consumption and enhance PU protection as well as channel utilization.

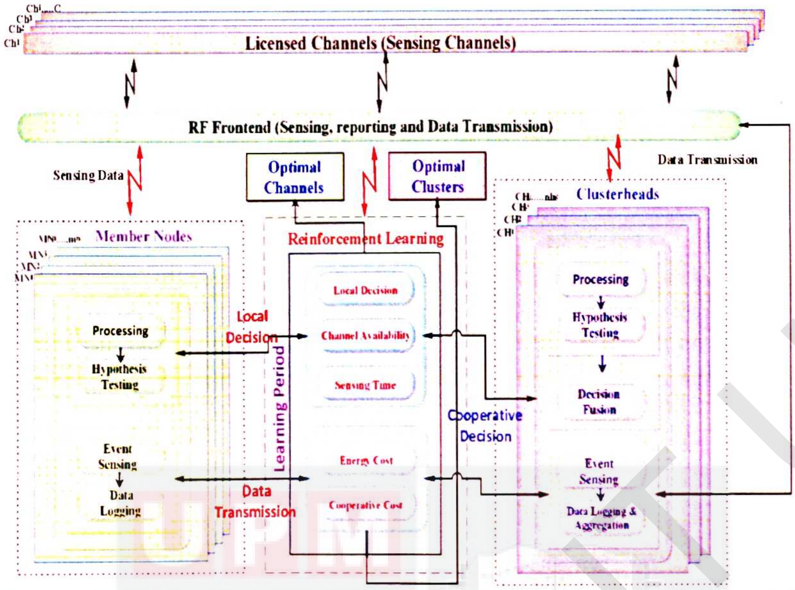

Figure 1.6: Illustration of the RL based network clustering framework.

1.6 Research Contributions

The main contributions of this thesis is towards realization of energy efficient data communications and dynamic spectrum access for cognitive radio sensor networks. This can be summarised as follows:

i. An energy efficient spectrum aware clustering algorithm that allows member nodes to learn optimal policy for choosing optimal cluster is developed. Specifically, each member node learns the local decision accuracy, cooperative sensing and data communication energy costs using RL and adapts to dynamic environment.

ii. A pairwise constraint that ensures only SUs with at least one common vacant channel with a tentative CH and within the CHs one hop radio range can form a cluster is implemented in spectrum-aware clustering to enhance channel sensing performance.

iii. The pairwise constraint based clustering algorithm is compared with groupwise constraint based algorithms in which remarkable performance improvement in terms energy efficiency, channels sensing performance and computational complexity is achieved.

iv. A model of network energy consumption comprising of cooperative channel sensing, inter-cluster and intra-cluster data communication energy consumptions is derived and optimal number of clusters that minimizes network energy consumption is determined.

v. A weighted hard combination scheme that improves cooperative detection performance while reducing communication overhead and energy cost for reporting sensing results. The scheme utilizes features of both quantized and hard combining schemes to balance trade-off between detection performance and communication overhead.

vi. An energy efficient RL based scheme that determines optimal sensing order and optimal set of channels has been developed. The scheme allows SUs to learn channel conditions and determines optimal solution that minimizes channel sensing energy cost and enhances PU detection as well as channel utilization. It considers not only channel availability and local decision accuracy but also the expected energy cost for accessing the channel.

1.7 Thesis Outline

The thesis outline and the reading sequence are illustrated in Figure 1.7, the preceding chapters are organized as follows. Chapter 2 essentially provides background information on the techniques and algorithms introduced in the thesis and reviews previous works related to this thesis. The chapter first introduced the concept of CR and its main elements. Dynamic spectrum access and spectrum sensing techniques are then introduced, their features and drawbacks are summarised. Network clustering and energy optimization as key approaches for efficient communications in cognitive radio sensor networks are introduced and finally machine learning and RL approaches as means of addressing dynamic channel access and energy challenges in cognitive radio are introduced. In Chapter 3, RL based clustering algorithm is devised for network energy optimization and primary user detection enhancement. Weighted decision fusion and RL based cooperative channel sensing scheme for addressing energy and channel sensing challenges in cognitive radio are introduced in the chapter. In Chapter 4, simulation results for the proposed schemes are presented and analysed. Performance evaluation of the schemes in terms of energy consumption and PU detection performance are presented and compared with established bench mark in the literature. Chapter 5 presents conclusion and recommendations for future research direction.

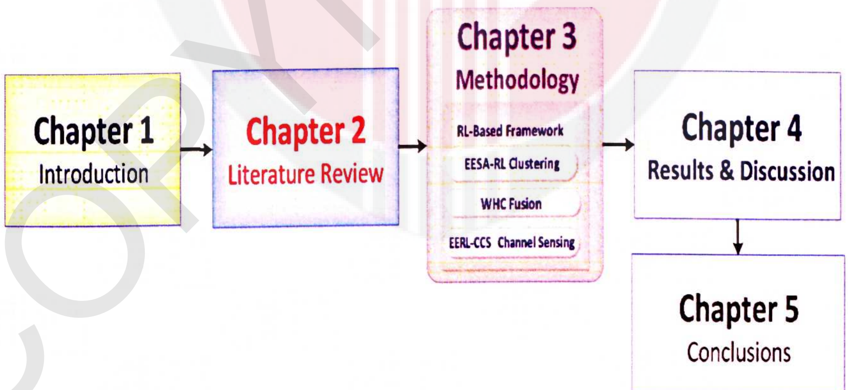

Figure 1.7: Organization of the Thesis.

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