A new cross-layer design strategy for TV white space cognitive radio applications

Conference or Workshop Item

A New Cross-Layer Design Strategy for TV White Space Cognitive Radio Applications

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***Abstract-*: Conventional single layer processing in *Cognitive Radio Networks* (CRN) can incur significant time costs in transferring information between the various layers of the *Open System Interconnection* (OSI) model, due its innate sequential structure. This is especially a problem for CRN which usually only has a narrow time window to access spectral gaps of either licensed or other secondary users (SU). To exploit this opportunity, *cross layer processing* (CLP) paradigms that share information between OSI layers and the radio system have been proposed to maximise throughput for SU, while maintaining *Quality of Service* (QoS) provision to the licensed primary user. With the global transference of TV systems to digital platforms, regulatory bodies have identified an opportunity to allocate additional digital TV (DTV) channels to CRNs on a localised basis, in what is called *TV White Space* (TVWS). This paper investigates how CLP of information can be effectively exploited to enhance CRN system performance by making key channel allocations to minimise disruption to the spectrum environment, while maximising available resources to fulfil application and network requirements within TVWS.**

I. INTRODUCTION

Both the Office of Communications (Ofcom) in the UK and the Federal Communications Commission (FCC) in the US have recently adopted rules allowing new broadband devices to operate in unused television bands, popularly known as *TV White Space* (TVWS) [1]. In the UK, following the digital switchover, there are now designated portions of the interleaved TV spectrum which enable coexistence between both licensed *primary users* (PU) and unlicensed *secondary users* (SU) at particular geographical regions. In [1], it was stated within the UK, 50% of locations can release up to 150MHz of spectrum and from 90% of locations 100MHz is to be designated as TVWS. A corollary of this is *cognitive radio networks* (CRN) wishing to exploit TVWS must be able to allocate non-contiguous channels to its users. It has been shown [1] that the maximum contiguous channel capacity is 16MHz, so to secure greater capacity, non-contiguous *Orthogonal Frequency Division Multiplexing* (OFDM) techniques need to be employed. While this makes TVWS bands attractive and a leading candidate for opportunistic spectrum access using CRN technology, there are key design challenges still to be resolved:

1) The avoidance of PU interference which is deemed mandatory for *cognitive radio* (CR) deployment.
2) Once a vacant channel has been identified, correct resources need to be allocated to the RF channel to uphold the requisite *quality-of-service* (QoS) across all OSI layers in an efficient and intelligent way.

Cross layer processing (CLP) design strategies attempts to optimise key parameters by using information from other OSI layers, allied with information that is not readily available within the OSI communication stack to address these challenges [2]. Unlike normal OSI stack information exchange, CLP is not constrained to information that is of necessity, contained within adjacent layers. This enables faster information retrieval because the information does not have to be transferred through several layers before reaching the layer where it is required. Furthermore, not all information required within a layer to perform its function is passed to other layers, so CLP permits information to be utilised by any OSI layer.

This paper proposes a management system comprising of cross-layer blocks which interface to each OSI layer and hence are able to make faster decisions based on inter-layer information whilst being adaptive to the environment. A new architecture called the *Cross Layer Cognitive Engine* (CLCE) is introduced which applies fuzzy rules as part of an *enhanced detection algorithm* (EDA) to enable key channel allocation decisions to be made to minimise disruption to the TVWS environment. Initial findings exhibit promising improvements in detection performance in terms of both *signal-to-noise ratio* (SNR) and transmitter distance for the CLCE model in the TVWS relating to the Bristol (Mendip) TV transmitter in the United Kingdom.

The remainder of this paper is organised as follows. Section II provides a review of existing CLP techniques as well as some of the main design challenges, whilst the new CLCE implementation is discussed in Section III. Section IV provides details of the test models, with Section V presenting some initial results. Section VI gives some concluding comments.

II. REVIEW OF EXISTING WORK

Conventionally the OSI model passes information serially between layers, which inherently introduces latency into the decision making process [4], [5]. This has not been a major issue so far because CRN research has predominantly focused to date on the physical layer. As the emphasis shifts however, towards optimising the available resources to improve the QoS for the end-user, so CRN systems need to concomitantly influence parameters in different OSI layers. Examples range from optimising RF power for routing through to dynamic spectrum access decisions which are tailored to the requirements of layer 5. Some of the main challenges in realising the CLCE paradigm [4-6] are:

Modularity – OSI layers are designed to be modular so they operate independently of each other. Cross-layer design can compromise this requirement so avoiding technology-specific parameters being passed to the CLCE by abstraction helps alleviate the need for a tailored design in different cross-layer blocks.

Information Interpretability – Choosing a knowledge representation base which is able to accommodate different implementations of the layer modules is vital.

Dealing with Imprecision and Uncertainty – Since parameters to be exported may have measurement inaccuracies, cross-layer blocks need to be able to manage imprecision, such as having fuzzy capability.

Complexity and Scalability – As CR can operate with different wireless configurations, to optimise the wireless link to user requirements, the cross-layer block can become complex because of the number of possible parameters that will need to be exported.

Several approaches for implementing CLP blocks have been previously proposed [3], [6], and [8] with their respective advantages and drawbacks being outlined as follows:

Radio Knowledge Representation Language [8], [9] - Each micro-world represents a specific wireless technology which implies the CLCE needs explicit knowledge about these technologies. This is contrary to the aforementioned modularity and scalability features.

Artificial Intelligence (AI) [5], [8], [10] - established solutions like genetic algorithms and neural networks are well suited to handling large sets of variables, but they generally require long supervised learning times which is not practical for wireless applications.

Fuzzy Logic Controllers [5], [6], [8] – technology-specific information is kept in the OSI layers with a more generic information representation base used in the CLP such as energy sensing values in a channel. Improved information interpretability by exploiting linguistic attributes for membership functions. Precision and accuracy issues are avoided by using what is an imprecise knowledge representation base. Fuzzy Logic Controllers require low computational power and dedicated Fuzzy Logic Controllers can be used for critical scenarios in a distributed architecture.

Since fuzzy logic fulfils many of the essential requirements of a CR-based CLP for TVWS applications, allied with relatively being straightforward to implement and incurring low computational overheads. The rest of this paper will consider the fuzzy logic option for achieving improved channel allocation within the CLCE design.

III. THE CROSS LAYER COGNITIVE ENGINE (CLCE)

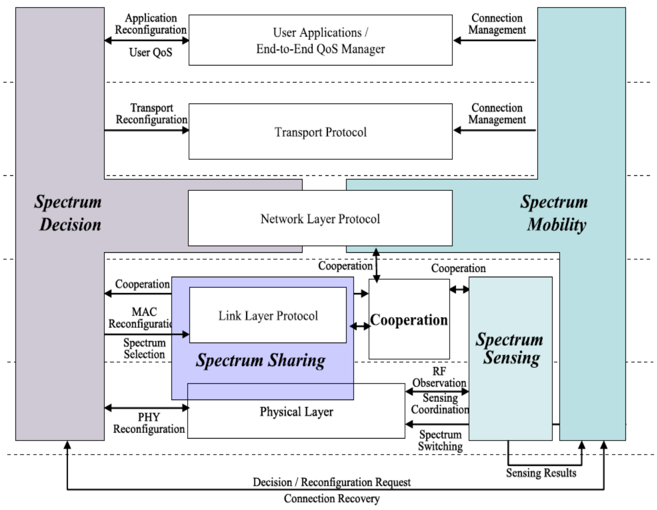

Figure 1: Block diagram of a generic *Cross-Layer Cognitive Engine* (CLCE) architecture [2]

The CLCE has the generic cross-layer architecture [2] shown in Figure 1, with the various blocks undertaking the following functions:

i) *Spectrum sensing*: this block transmits the energy sensing measurements from the physical layer to both the *spectrum decision* and *spectrum mobility* blocks.

ii) *Spectrum decision*: this block makes the decision as to whether a particular channel is vacant.

iii) *Spectrum mobility*: this block manages channel handoffs in the event of a PU becoming active during a SU session.

iv) *Spectrum sharing*: this block controls channels access in the event of multi-user SU requests.

This paper concentrates upon designing the CLCE to achieve better channel allocation decisions, so the blocks which have

been implemented in the CLCE are those directly relating to spectrum mobility, spectrum decision and spectrum sensing.
The initial CLCE implementation aimed to improve the detection probability for a licensed DTV transmitter. This was achieved by exploiting *a priori* information about the DTV system and sharing this between the MAC and physical layers together with the cognitive cycle in making a spectrum access decision. The net outcome from this CLP is to transform an energy sensor into a feature sensor, which as will be evidenced in Section V, consistently provides superior performance compared to a stand-alone energy sensor.

The first parameter to be defined is the noise floor. The DVB-T transmission mask [11] defines this as -115dBm, although this can fluctuate between locations, but since this is the average value adopted by Ofcom, it is assumed in all experiments. The next step is to define the various detection transitions covering the signal range from noise through to weak *uncertain* and strong signals. Figure 2 displays this range which formed the basis of both the *enhanced detection algorithm* (EDA) and embedded fuzzy rules. The different detection ranges assumes a mobile sensor of height 1.5m using Channel 59. In setting the detection thresholds, the *unoccupied* range lies between the noise floor (-115dBm) and the sensor output which yields a threshold *bit error rate* (BER) lower than $2x10^{-6}$, which is generally considered [14] as the peak BER to achieve satisfactory TV picture quality and thus is the maximum range achieved using diffraction propagation. The *uncertainty* band is defined between the sensor outputs at the aforementioned BER threshold through to the sensor output at 64Km, which is the maximum range for *line of sight* (LOS) propagation for the mobile sensor. The third *occupied* band is defined from the LOS sensor output at 64Km and below.

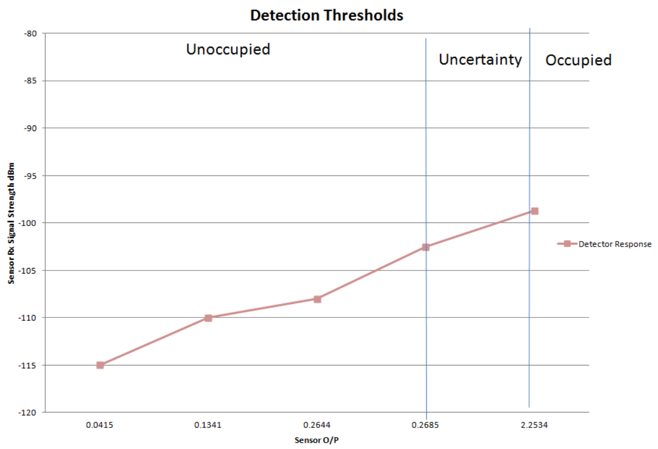

Figure 2: Noise power versus sensor output

Figure 2 reveals the requisite thresholds which are defined such that if the sensor output is less than 0.2685, then it is considered *unoccupied*. If it lies between 0.2685 and 2.2534 it is classified as *uncertain* and above 2.2534, it is deemed to be *occupied*. These two threshold values were respectively determined from: i) the Channel 59 sensor output at 82 Km which is the $2x10^{-6}$ BER threshold; and ii) at 64Km which is assumed as the useful signal limit since this lies at the extremity of the LOS and is where propagation beyond this value is predominantly due to diffraction. For comparative purposes, a *basic RF detection* algorithm has been also implemented in which the cut-off for detection was stipulated as the Channel 59 LOS sensor output at 64Km and which simply applies a binary decision i.e., either ON (*occupied*) or OFF (*unoccupied*) with no *uncertainty* state available.

The EDA scans 5 channels up and down from the channel under investigation and if this particular channel lies within the *uncertainty* range and any other channel 5 up or down also lies within either the *uncertain* or *occupied* detection ranges, then the outcome is weighted according to the fuzzy rules. This reflects the fact DTV channels in a local area are generally deployed in a cluster configuration in which another DTV channel either 5 channels up or down can be located.
Figure 3 shows the fuzzy logic inference model for EDA, which adopts the classic fuzzy logic framework [6], so the I/P A is the sensor output for the channel under investigation and the I/P B is the maximum sensor output for either 5 channels up or down from the reference channel.

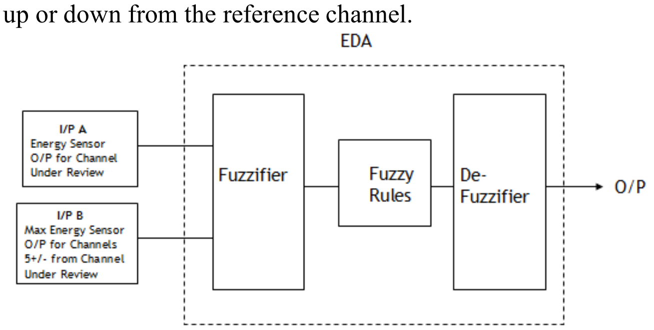

Figure 3: The *Enhanced Detection Algorithm* (EDA) model

The role of the fuzzifier is to translate the input into a fuzzy set which is allocated a membership function. This can follow any defined function within MATLAB [7], but in this scenario a normal (Gaussian) probability function is used for RF detection. The corresponding energy membership functions for the input variable I/P A and the input variables I/P A and I/P B are displayed in Figure 4.

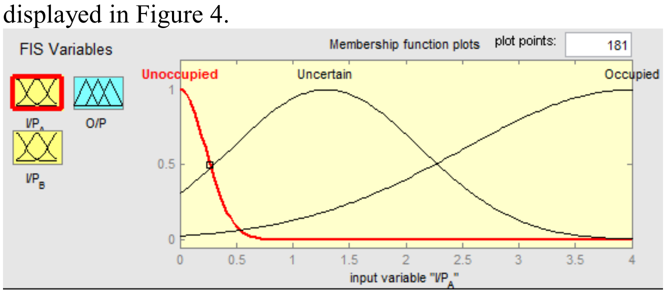

Figure 4: Channel RF energy membership functions

These membership functions are derived from Figure 2 with the sensor output thresholds coinciding at probabilities of 0.5.
The following five fuzzy rules are then applied to the two EDA input energy values, I/P A and I/P B in Figure 3:

1. IF (I/P A) = unoccupied THEN (O/P) = unoccupied.
2. IF (I/P A) = occupied AND (I/P B) ≠ unoccupied THEN (O/P) = occupied.
3. IF (I/P A) = uncertain AND (I/P B) ≠ unoccupied THEN (O/P) = occupied.
4. IF (I/P A) = uncertain AND (I/P B) = unoccupied THEN (O/P) = unoccupied.
5. IF (I/P A) = occupied AND (I/P B) = unoccupied THEN (O/P) = unoccupied.

These five rules govern the complete behaviour of the EDA in classifying the various channel energy measurements. The final block is the de-fuzzifier where a crisp output is produced using the *centre of area* method [7]. The de-fuzzifier output (O/P) follows a linear function, so 0 to 0.5 represents an *unoccupied* channel, while 0.5 to 1 reflects that it is *occupied*.

IV. TEST MODELS

Two different test models for CLP techniques were considered, namely a basic RF and a fuzzy logic model. The latter was discussed in Section III, while the RF model can be divided into three different types: i) the Digital TV (DTV) transmitter-receiver pair, ii) the CR transmitter pair and iii) the sensing platform. All three have been designed and implemented in Matlab/Simulink [7] and have the following functionality:

i) The DTV transmitter–receiver pair is based upon the Bristol (Mendip Transmitter) TVWS channel patterns [11] and generates the DTV signals for the simulations in Section V. It comprises a mixer subsystem which sets the transmitter frequency and power. The receiver where the noise parameters are set contains a super-heterodyne mixer and linear equaliser to correct carrier misalignment.

ii) The CR transmitter-receiver pair simulates CR signals and has an OFDM architecture. The CR pair has the same core design as the DTV pair in i) but additionally includes an OFDM module to enable CR to operate in TVWS to increase capacity.

iii) The RF energy sensor employs a receiver block similar to that used in both i) and ii), but instead of the baseband blocks, a Fast Fourier Transform is applied to implement energy detection.

The propagation paradigm used in the above models are based upon the Egli model [13] which mimics losses over irregular terrains and the *knife edge* diffraction [13] model for distances which lie beyond the LOS.

V. DISCUSSION OF RESULTS

The performance of the EDA was compared with a basic RF energy detector, using the test platform shown in Figure 5. The following series of results were thus collated for distances of between 58Km to 95Km from the transmitter and channels 58, 59 and 61, thus incorporating both high and low powered TV channels. The DTV channel specifications for the Bristol (Mendip) transmitter used in this results analysis to define TVWS are given in Table 1.

TABLE 1
Mendip Transmitter Channel Allocation

C54 (738MHz)	C55 (746MHz)	C56 (754MHz)	C58 (770MHz)	C59 (778MHz)	C61 Temp (794MHz)	C62 Temp (802 MHz)
100KW 64 QAM 24Mb/s	10KW 64 QAM 24Mb/s	10KW 64 QAM 24Mb/s	100KW 64 QAM 24Mb/s	10KW 64 QAM 24Mb/s	100KW 64 QAM 24Mb/s	10KW 64 QAM 24Mb/s

The test platform used for channels 58, 59 and 61 is shown in Figure 5.

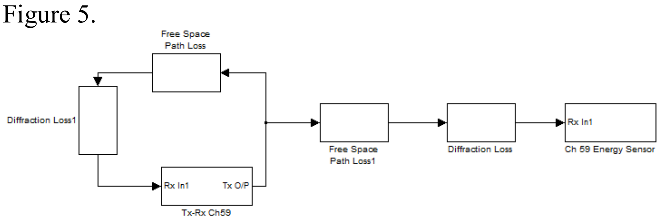

Figure 5: Test platform for Channels 58, 59 and 61

The corresponding detection results for various transmitter distances are plotted in Figure 6. The detection probabilities were calculated by taking sensor readings over the range from 58Km to 95Km and using noise values of between -115dBm and -80dBm. The probability of detection was taken from the output of basic and *enhanced detection* algorithms, with positive detections being normalised by the number of data points to give the corresponding probability for a particular distance. The results clearly show both algorithms achieved a probability of 1 with the former up to 58Km and EDA up to 66Km. By comparing the corresponding received signal values at these two distances, from Figure 6 it can be seen a net 11dB SNR improvement has been achieved by EDA to corroborate the rationale for applying fuzzy rules for channel allocation in the CLCE design.

Interestingly, in [12] where the detection probability was calculated for a 2.4GHz channel using an energy detector and co-operative sensing mechanism, a SNR improvement of only 2dB was achieved, compared with the 11dB achieved by the new EDA-based approach.

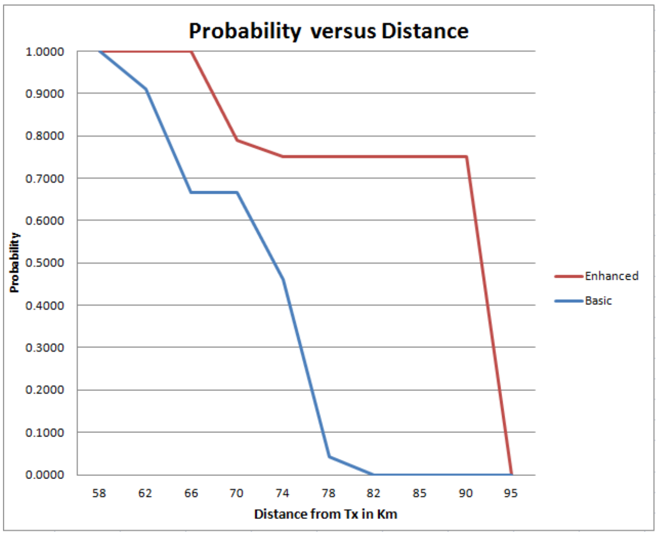

Figure 6: Detection probability plots

The next series of experiments investigated the occurrence of false PU detections in TVWS. Using the same test platform used for the detection probability, it is assumed that a CR source is now transmitting on Channel 59 at 4W, which is the maximum proposed FCC power level for a CR in TVWS with no adjacent channel transmissions. The RF signal from this CR is sensed at various distances between 1 and 20Km using both the basic and EDA models. The corresponding false detection results are shown in Figure 7.

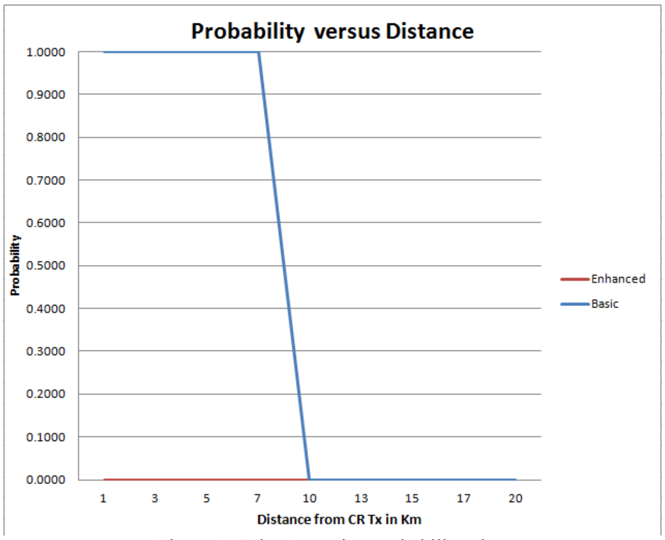

Figure 7: False Detection probability plots

It can be seen from Figure 7 that the basic algorithm falsely detected the CR as a PU over the range 1Km to 7Km, while in contrast the EDA did not incorrectly detect any PU, because there was no adjacent channel correlation (see fuzzy rule 5).

The advantage of the proposed CLP strategy of using physical layer sensing information to shape how the MAC layer accesses channels is counterbalanced by an increase in sensing time. This was typically 53ms per sensing cycle which gave a total overhead of 0.583s for adjacent channel sensing. Given the inherent static nature of DTV transmissions, this is not a significant impost because the CR source is not seeking to opportunistically exploit short intermittent periods when the PU is not transmitting, so the time incurred to engage a TVWS channel is not critical.

VI. CONCLUSION AND FUTURE WORK

This paper has demonstrated that by sharing cross layer information across the physical and MAC layers, the probability of TVWS primary user detection can be improved compared with that achieved using a stand-alone RF energy detector. To achieve this, a *Cross Layer Cognitive Engine* (CLCE) implementation using fuzzy logic has been designed incorporating an *enhanced detection algorithm* (EDA) for DTV channel allocation. The CLCE was conclusively been shown to outperform the basic energy detector by up to 11dB as demonstrated in the transmitter distance probability results. Further testing and analysis are required to be conducted to evaluate whether the improved performance achieved by EDA for the Bristol (Mendip) transmitter, can be repeated in other TVWS areas of the UK. Furthermore, consideration will be given to combining EDA with co-operative sensing in an attempt to address the recurring *hidden node* problem.

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