

Enhancing Cognitive Radio Network Through the Novel Optimization Process and Deep Learning Model in the Transverse System

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Abstract:

The dynamic distribution of spectrum, made possible by next-generation networks that utilise Cognitive Radio technology, helps to alleviate spectrum shortages. Additionally, these networks may be dynamically operated to save energy. The innovative cloud-sharing-decision-based method for optimising cognitive radio networks' wireless networks is introduced in this research. Optimisation was achieved via 3 key performance indicators: spectrum utilisation, power utilisation, and human revelation. Researcher find the best key performance indicators for a realistic India's suburban situation. An optimisation technique in the cloud-based design for architecture simultaneously decreases networks power usage for about 27.6%, mean worldwide revelation by 34.4%, & spectrum utilisation for about 34.6% when related to a standard Cognitive Radio net. For the areas of networks power consumption (4.9%), spectrum utilisation (7.4%), and global exposure (4.4%), method outperforms the old design, even in the worst-case optimisation scenario.

Keywords: Cognitive radio network, Spectrum utilisation, Deep learning model, Global exposure, Cloud-sharing-decision

1. Introduction:

The insufficient supply of spectrum to meet the increasing growth in wireless traffic demands has been recognised as significant issue in the wireless communication sector. Unexpectedly, several comprehensive spectrum utilisation measuring efforts have shown that the majority of the RF spectrum is either unused or underutilised. These spectrum assessments conducted in cities globally indicate that the mean utilisation of the sub-3-GHz spectrum, in terms of both spatial & temporal dimensions, never exceeds 21%.

By taking use of underutilised or unused spectrum, Cognitive Radio has emerged as a versatile solution to the problem of spectrum scarcity in this setting. Efforts have been made to use the white spaces in

television broadcasts via research on cognitive radio technology. TV white spaces (TVWS) were areas of the frequency spectrum which are not in use by a main licensed service (often TV broadcasting) in a specific place at a certain time. The secondary gadgets' cognitive radio characteristics and technology needs over dynamically access these TVWSs. Regulatory authorities permit opportunistic spectrum access for these devices, provided that they acknowledge interference from main licensed services and do not disrupt such services. However, they are not permitted legal usage of the spectrum. Cognitive radio network deployment performance indicators include the degree to which these devices cause interference with one another.

Cognitive radio has also been suggested as a way to make more efficient utilisation the existing radioelectric spectrum of Long-Term Evolution (LTE) systems. With LTE-U, for example, users may pool their frequencies in the unlicensed ISM band to alleviate 4G mobile network congestion and spectrum scarcity. Indian Telecommunications Standard Institute examines the usage of LTE Cognitive Radio Systems operating under UHF band TVWS in the technical study TR 103 067/2014. One common use of LTE's cognitive capability for exploiting opportunities in the UHF TV spectrum is the coexistence of LTE with TV broadcast systems, which is being studied.

Due to "spectrum scarcity," the highest frequency bands are the only ones that can meet the capacity demands of 5G networks and next-generation radio. Consequently, many uses of 5G networks are constrained in low-population regions, such as rural areas, small suburban communities, and so on. Researchers have also looked at the potential of 5G networks that use Cognitive Radio & carrier aggregation to provide rural regions with wideband connectivity. Since this is the case, Cognitive Radio is an essential tool for the next generation of radio.

For situations in heavy user density, interference control has proven to be a significant difficulty with Cognitive Radio. Evaluating the balance among interference & spectrum efficiency is not entirely possible with the standards that are presently in place. For instance, in order to allocate spectrum further, user devices along with base stations (BSs) are not required to meet any spectrum sensing criteria by IEEE 802.11f. Geolocation records can help keep interference to a minimum for main approved services like digital TV broadcasts. Spectral sense and allocation management must be put in place, though, to make sure that Cognitive Radio systems on the same net or on other net does not cause problems. Geolocation records can help keep interference to a minimum for main approved services like digital TV broadcasts. Research on spectrum utilisation and measurement initiatives provide the basis of these datasets. The possible success of cognitive radio networks in sharing spectrum is therefore diminished due to the lack of constantly updated knowledge about spectrum utilisation. Some recommendations and required channel sensing criteria. To provide just a few examples, it specifies the bare minimum for things like scheduling sensing windows and quiet intervals, the highest interference thresholds for various signal kinds, and the necessary reporting of discovered interference by users' devices. Nevertheless, a set of required sensing methods is not provided.

Numerous advancements in spectrum sensing methods to mitigate interference have been documented in recent years. Nonetheless, no significant progress has been documented in architectural and dynamic network optimisation, which constrains the potential for improved trade-offs between interference control and spectrum utilisation efficiency. Spectrum sensing methodologies for cognitive radio

applications are often categorised as blind approaches (i.e., those that do not consider signal properties) along with signal-specific sensing techniques. The fundamental spectrum sensing technique used in cognitive radio signals is Energy Detection. The accuracy of energy detection is based on previous information about the noise level. The level of noise at the detector is influenced by several variables, including temperature fluctuations, calibration inaccuracies, and changes in low noise amplifier gain. Signal-specific sensing methods often rely on the correlation between a received baseband signal and a reference pattern. This indicates that some the demodulation for the signal is necessary. Consequently, the complexity of the hardware and the necessary sensing duration increase.

Learning algorithm is introduced on the way to enhance spectrum exploration and minimise interference from cognitive radio devices. A cooperative scheme is also presented for sharing spectrum that relies on data generated by secondary Wi-Fi node locations. To maximise network throughput, the algorithm takes into account the user's device behaviour history and allows for variable sensing times.

Key performance indicators (KPIs) for the network have not seen any improvement in terms of design, medium access, or connection efficiency. A new cooperative system that uses an IoT design to make effective use of TVWS. via the integration of spectrum sensing and a quality-of-service feedback method executed by logic for control in the IoT social platform, the suggested layered architecture improves coexistence concerns and safeguards the key services. One potential solution to the problem of inefficient spectrum consumption and coexistence among services that use the same bands of frequencies (such as the VHF and UHF bands) is for the main and secondary services to work together.

Key performance indicators for networks include, but are not limited to, power consumption and human exposure to radiofrequency radiation. There is a strong correlation between these metrics and the impact that ICT has on the environment. Therefore, optimising electrical consumption and exposure is also necessary to achieve environmentally friendly wireless networks. But these parameters necessitate weighing the pros and cons. offers a way to quickly find the best parameters for a wireless experiment that take many objectives into account.

The optimisation of next-generation Cognitive Radio networks with respect to many objectives is the innovative aspect of this study. A cloud-based design, which enables all network devices to share the sensed information, is being considered as an alternative to the conventional dispersed architecture for spectrum management. A more efficient network with lower power consumption, spectrum utilisation, and overall exposure may be achieved by dynamically optimising the network using the collective intelligence of all devices. Improving the network's key performance indicators and decreasing adverse impact from/to the principal licensed service requires dynamic optimisation. To the best of the researcher's knowledge, no previous study has optimised Cognitive Radio networks such that power use, spectrum usage efficiency, and exposure are all considered.

Following is a synopsis of the paper. Section 2 details the proposed cloud-based architecture for Cognitive Radio network management. Also covered are metrics, a multi-objective optimisation algorithm, a real-life example, and some things to consider when first setting up a wireless network. The researchers provide a brief overview of Pareto Optimality and go into further detail about the reasoning behind them. Section 3, shows how the suggested design and method were used to improve

the network and compare the results to those of a standard Cognitive Radio network. In Section 4, the conclusions are given.

2. The technique:

2.1 Management of Cognitive Radio Networks Using a Cloud based Architecture:

In comparison to the conventional design (Fig. 1a), the Cognitive Radio network's suggested cloud-based architecture (Fig. 1b) will enable a greater degree of multi-objective optimisation.

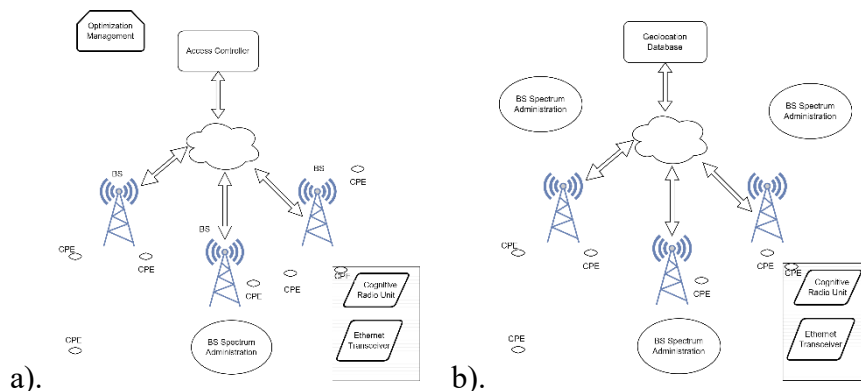


Figure. 1 Illustrates Cognitive Radio Network Architecture a) Conventional b) Cloud-based administration.

In the conventional Cognitive Radio networks design, Consumer Premise Equipment in the user-side includes the Cognitive Radio unit and an Ethernet transceiver. The BSs together with a BS management is also part of the design. This unit is responsible for managing the registration and monitoring of user data as well as the implementation of the spectrum management regulations outlined in the standard. Lastly, getting online and (if needed) accessing a geolocation database is made possible using an ethernet or optical fibre connection. As shown in Figure 1a, the execution of spectrum management rules, as well as the connection, registration, and monitoring of users, are overseen by each BS in this architecture. The data perceived by each BS, as well as data felt by users within their range, allows them to independently allocate spectrum. When it comes to bidding on channels, regulatory restrictions, and footprint constraints, the level of freedom of the BS are severely limited by the supply of a geolocation database. There are no real-time updates provided by this database as it depends upon static information from spectrum surveys. Perceived network interference and spectrum consumption efficiency are affected by changes in the propagation circumstances.

As shown in Figure 1b, the proposed architectural change for next-generation Cognitive Radio networks involves centralising the majority of management tasks, particularly those pertaining to spectrum management. All of the network devices may have their sensed data collected in this manner. In order to serve user traffic more efficiently in terms of network electricity usage, global reach, and spectrum utilisation, it is necessary to know and analyse the network performance metrics from the whole network. The BS data network transmits this data from every BS to the cloud, where it is received by the central Access Controller. Given the capacity of the backbone, presume that the signalisation data associated with Cognitive Radio functions is insignificant. Identical data is sent to

the BSs by the geolocation databases. Therefore, the standard-defined headers and interfaces do not need any change.

While distributed networks are often more efficient, they may become unstable if devices that make choices are impacted by devices that are outside their control. The idea of autonomous vehicle operation on 5G networks is comparable. With a Vehicular-to-Vehicular (V2V) communication network architecture, automobiles can only communicate with other cars in their immediate vicinity, leading to a rapidly unstable system (a cascade of crashes). This is due to the fact that every vehicle's control choice relies on its unique understanding of its surroundings. Any open-loop control system will experience the same thing, as would the classic Cognitive Radio network, whose interference is represented as a crash.

2.2 Finding the Optimal Pareto for Efficiency:

Optimal performance according to the Pareto principle was first used to address issues in economics and the social sciences. A Pareto optimum situation is one in which improving one goal (parameter) will always lead to a worsening of another. The goal of optimising multiple parameters simultaneously is common in engineering and is known as a multi-objective optimisation problem. It is feasible to discover a group of options which is Pareto efficient given a set of criteria to evaluate them. "The Pareto Front" describes this group. As a result, all parameters may have their ideal trade-offs determined by the design restrictions, situation, and application.

Throughput, energy consumption, delay, electromagnetic radiation, and spectrum utilisation are some of the competing performance metrics for wireless networks. If you want to maximise one parameter, you'll have to minimise another. In the vast majority of wireless contexts, this is clearly an undesirable state. The optimisation method may take into account several permutations for performance indicators, each given a particular weight (Pareto coefficient) according to Pareto optimality (for more on this, see Section 2.5). This allows us to express the generic Pareto equation P as a collection about n independent metrics g multiplied by a fixed weight w.

$$P(w_1; w_2; \dots; w_n) = \{w_1.g_1; w_2.g_2; \dots; w_n.g_n\} \quad (1)$$

For each combination of $w_1; w_2; \dots; w_n$ the subsequent condition must be fulfilled:

$$\sum_{i=1}^n w_i = 1 \quad (2)$$

Researchers estimate the solution set through Delaunay Triangulation to ensure a continuous Pareto front, since Pareto coefficients might take an endless number of values. Researchers use Pareto Optimality to a cognitive radio network to study a trade-off between three KPIs: human exposure, spectrum utilisation, & network power consumption.

2.3 Rationale:

Every node of a cognitive network is responsible for sensing the spectrum and relaying interference-related data to other nodes in the area. Nearby BSs get this data via a wireless connection that uses BPSK modulation on a self-sensed empty channel. As soon as a user requests a connection, the first base station (BS) handles the demand & provide the spectrum to register the user. Concept calls for a central access controller to monitor interference and allocate spectrum resources, with the BSs

presumably collecting this data. Refer to Figure 2 for steps on how to connect a single client with Cognitive Radio BS.

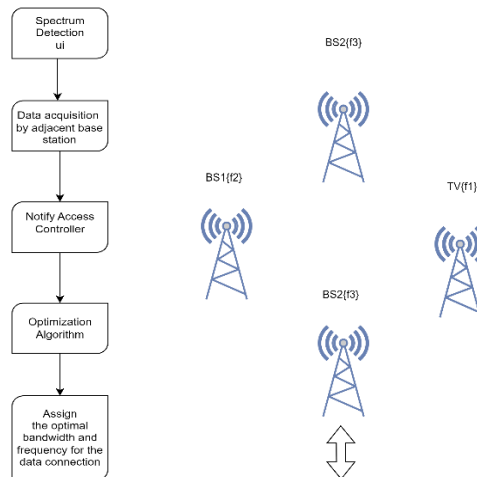


Figure 2: Flow diagram illustrates the process to connect a person with a BS at the cloud based Cognitive Radio design.

To begin, as shown in Figure 2, user devices u_i detects the spectrum and then reports any interference (I_1, I_2, I_3, \dots) that they see from other users, broadcasting stations, or other BSs for a central access controller. Users are also expected to provide geolocation data, information on the emitted signal, and any other criteria specified by regulatory bodies or the standard. Take note that the first connection is established with a nearby base station using BPSK modulation to minimise interference and any frequency that u_i perceives as free. The algorithm also has to look at the data sent from every user and BSs, compare the interference to the highest level allowed by the network (ISL [dBm]), and then fix the problem in order to choose the ideal link for u_i while taking the networks KPIs into account. ISL is the largest signal threshold where the program lets multiple BSs use the same frequencies. When it comes to sharing frequencies, there is one ISL limitation for TV broadcasting (shown in Figure 2) & another value for Cognitive Radio base stations (BS1 & BS2 in Fig. 2). Keep in mind that every user's spectrum allotment is finalised. The ISL limitation determines which frequencies a given BS may utilise to communicate with several users simultaneously. So, for example, BS2 and u_i have to talk on a frequency that neither BS1 nor TV are using (i.e., f_3) if the interference level is too high (see to Fig. 2). In every other case, it may recycle the previous frequency (f_1 or f_2).

A decrease in the quantity of base stations (BSs) significantly affects the minimisation of network power consumption as well as costs for greenfield network design. This is because cognitive radio base stations (BSs) do not vary in power consumption whether idle or under load, regardless of the amount of radiated power or the amount of traffic. As an example, the Cognitive Radio BS consumes 64W of power at peak traffic & maximum radiated signal strength, compared to 38W when there is no data transmission (idle power consumption equals 59%). A centralised access control design also permits the dynamic reactivation of a cluster of BSs. When turned off, Cognitive Radio BS uses a mere 9 W of power. But the power output per BS rises to reach the furthest users when the number of BSs is

reduced. Consequently, that cell's exposure rises. This manner, the optimisation algorithm may use a variety of optimisation tactics tailored to the specific characteristics that need improvement. In Section 2.5, the depth on the optimisation technique is explained.

2.4 Metrics:

Prior to optimising the algorithm for the key performance indicators (KPIs), establish the following metrics: network energy consumption, global exposure and spectrum utilisation.

The power usage plan for a Cognitive Radio BS is explained in order to take into account how much power the PC will use for the network design. Now, think of centralised access controller (see Fig. 1) as a power consumption factor in the network; at a specific point in time, it may put the BSs that aren't in use to sleep. When turned off, the Cognitive Radio BS—which includes the transceiver, optical backhaul, and radio unit—consumes only 9 W of electricity. It is important to note that not all components with power consumption can be put to sleep mode in the absence of centralised control.

Global exposure E_G is found by taking the average between electric field E_{51} and a 96th percentile for the field strength E_{96} throughout the whole covered area. This is done to get the most exposure at the middle and highest amounts. In other words, equal weight is given to E_{51} and E_{96} . This leads us to the following equation that characterises the E_G :

$$E_G = \frac{E_{51} + E_{96}}{2} \quad (3)$$

A grid of "test points" spaced 50m apart be located constructed throughout the whole map in order to determine the intensity of the electric field across the covered region. The electric field intensity is determined on every grid point by calculating the value of whole transmitter T_{xj} . According to Equation 4, the electric field E_{Tx} [V/m] caused by transmitter T_{xj} may be determined by taking the following values: Path loss PL [dB] from T_{xj} at the grid point, the frequency f [MHz], and the corresponding isotropically radiated power [dBm] of T_{xj} .

$$E_{Tx_j}(x, y) = 10 \left(\frac{EIRP_{Tx_j} - 43.16 + 20 \cdot \log_{10}(f) - PL_{Tx_j}(x, y)}{20} \right) \quad (4)$$

Researcher find out how much each emitter adds with the power in the electric field at all grid point (x, y) via adding up each square of the electric field strength from each T_{xj} and then adding them up.

$$E_{total}(x, y) = \sqrt{\sum_{j=1}^n [E_{Tx_j}(x, y)]^2} \quad (5)$$

in which the sum of all transmitters is represented by n . Therefore, it is presumed that there is no phase connection between the field vectors created in each source.

In this deployment situation, the spectrum use is the number of channels needed by the networks to settle entire simultaneous connections.

$$S_U(u_i, BS_j) = \sum_{ch=1}^{S_{max}} k_{ch}(u_i, BS_j) \quad (6)$$

when $k_{ch} = 1$ denotes that the channel ch is associated with a communication connection between a BS_j and a minimum of one user u_i , and 0 otherwise. In accordance to the regulatory domain, the maximum amount of channels that may be employed is S_{max} . Reusing channels for communications between each user & the BS is how spectrum optimisation is done. By comparing the BS with user locations, the metric S_U may be used to quantify the spectrum occupied. The spectrum is accessible at the most appropriate frequency by each user device on an as-needed basis. Multiple frequencies may be used by a single BS to interact with its linked users. Once the interference constraints (ISL) are met, the frequency channels may be utilised.

Define the available white space across the whole area so that alternative solutions may be fairly compared.

$$W_a(x, y) = S_{max} - S_{UTx}(x, y) \quad (7)$$

The available white space is defined across the whole area so that alternative solutions may be fairly compared.

Once access manager gave the spectrum to every links among BSs & customers, including TV stations, the white area was open for accessibility, W_a indicates the channel numbers accessible at all grid point (x, y) . Whole area is split in points of the grid with coordinates x, y (taking into account an accuracy of 50m) in order to calculate this value. The disparity W_a occurs among the total amount of channels (S_{max}) & the channel numbers at all grid point via TV broadcasting service S_{UTx} , Cognitive Radio network devices, and other sources. You'll see that S_{UTx} also covers the spectrum utilisation for television transmission, while S_U just accounts for the usage of the Cognitive Radio network. W_a therefore denotes the region's residual channel availability. It is possible to compute the average amount of white space available by taking W_a into account across all grid points.

2.5 Algorithm for Multi objective Optimisation:

The network optimisation technique (i.e., goal KPIs) that will be utilised to minimise network energy consumption, spectrum utilisation, and exposure is described in technique 1. The method is based on capacity and is heuristic. As a result, a solution may be found to solve the optimisation issue but cannot guarantee an exact optimum network solution. The advanced average of each optimised network KPI has a maximum standard deviation of 3%, which indicates the convergence of the solution. Note that the underlying method given in does not incorporate spectrum management or interference. Therefore, adjustments were made to the multi-objective optimisation objectives for this study.

Input parameters include the users and the traffic needs. Before giving each user a traffic load, the algorithm makes sure that all the users in the area are spread out evenly and somewhat randomly (see Phase 1 line 2 of Algorithm 1 and Section 2.6 for details on the starting values about the input parameters). The whole procedure is iterated up to a maximum of Sim , which you may have seen. The greenfield planning involves optimising a set of baseline BSs (see to Section 2.6 for the beginning values of the input parameters) to determine the optimal BS placements (as measured by average route

loss to users) and the minimal number of BSs (NBS). The ideal placement of BSs is determined by the likelihood of achieving the lowest route loss to users, as shown in Phase 2 lines 6–14 of Algorithm 1, and a histogram containing the total amount of connections resolved through each BS over a series of simulations is generated (Max_Sim). Aiming at a standard deviation of less than 3% to represent the progressing average of the KPIs, the amount for simulations Max_Sim is experimentally selected. According to line 15 of Phase 2 of Algorithm 1, the initial phase's output is a set of new NBS for ideal BS locations.

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Phase 1:
Input: users, traffic, BSs, TV
1: while Sim < Max_Sim
2: Generate (users, traffic, BSs, TV)
3: end while;
4: while Sim < Max_Sim
5: for ui < users
6: for BSj < BSS
7: PL = Path_Loss (ui,BSj)
8: if (PL < Actual_Path_Loss) && Bitrate < Max_Bitrate
9: Best_BS (BSj)
10: end if;
11: end for;
12: Histogram [Best_BS]++;
13: end for;
14: end while;
Output:
15 Best_BS_locations get_Histogram(NBS)

Phase 2:
Input: Best_BS_locations;
1: Generate (Best_BS_locations);
2: while Sim < Max_Sim
3: for ui < users
4: for BSj < BSS
5: Calculate_Power_Consumption (ui,BSj);
6: Calculate_Exposure (ui,BSj);
7: Evaluate_ISL;
8: Set_Spectrum_Allocation (ui,BSj);
9: if Fit (u,BS) > current_fit
10: if Active (BSj) && Bitrate (BSj)
11: connect;
12: end if;
13: end if;
14: if unconnected
15: set_active BS (best_fit);
16: connect;
17: load_balance;
18: end if;
19: end for;
20: end for;
21: for ui < users
22: while connected (ui)
23: BS_Radiated_Power--;
24: end while;
25: end for;
26: calculate_Wa. (Network_Solution);
27: generate (Network_Solution);
28: end while
Output
29: Network_Solutions;
    
```

Phase 2 takes the Best_BS_locations collection of BSs as input. Similar to Phase 2, there are the same numbers of users and traffic densities. This step involves optimising the network in real-time. With Max_Sim and ui as inputs, the algorithm determines the fitness score for each potential connection BSj based on the overall number of simulations. Algorithm 1's Phase 2, lines 5–8 determines the optimal spectrum allocation for each established link by calculating power usage and exposure, only after considering a specific interference signal level limit (ISL). Interference levels are determined using the radiated power and route loss estimates for the network modelling and optimisation. To begin, researcher assess the available frequencies and select the lowest one that will allow the signal to propagate the best. The program will first check to see how much influence there is around the user & BS by considering all users, BSs and TV broadcasting towers in nearby areas. All devices' data may be retrieved via a centralised access infrastructure, which makes this feasible. Based on the data supplied by all users' BSs, a selection of frequency assignment is made. In classic Cognitive Radio net, the BSs are responsible for allocating frequencies based on static data imported through a geolocation database with the information about interference levels supplied by users alone within their range.

The fitness function fit (Phase 2, line 9 in Algorithm 1) looks at the net power usage PC [W], global exposure EG [V/m], as well spectrum utilisation if user ui and certain BSj are connected (refer Section 2.4 for a description of all measures).

$$fit(u_i; BS_j) = w_1 \left[1 - \frac{P_c}{P_{max}} \right] + w_2 \left[1 - \frac{E_G}{E_{max}} \right] + w_3 \left[1 - \frac{S_U}{S_{max}} \right] \quad (8)$$

The maximum power (Pmax [W]) used by the network is determined by all active BSs having a high radiated power, and the high exposure across the measured region, denoted as Emax [V/m], is also

determined by the same network circumstances. This ensures that no parameter is overestimated and that all performance metrics are normalised. Therefore, in the most extreme scenario when $P_C = P_{\max}$, $E_G = E_{\max}$, and $S_U = S_{\max}$, the fitness function is zero. A , w_2 , and w_3 are the weight factors. These percentages, which are equivalent to the Pareto coefficients, may take on values between zero and one. It is necessary to test several weight combinations in order to find the Pareto optimum solution. Therefore, the resolution of the weight components determines the number of simulations run. Researcher take into account a Pareto coefficient resolution of 0.25, which gives us fifteen fitness functions for every $(u_i; BS_j)$ potential link. Keep in mind that the total of all possible combinations of coefficients (w_1 , w_2 , and w_3) must be 1.

In Phase 2, lines 9–13 of Algorithm 1, each user is linked to the BS that has a high fitness value in terms of less power use, frequency usage, and exposure. This is provided that the BS is also capable to manage the user's speed. The active bit rate is changed at the one with a high fitness value when the user asks for a higher bit rate compared to what is now available. By transferring existing users to this newly active BS, researcher may distribute the network load more evenly (Phase 2, lines 14–18 in Algorithm 1). After every user has been assessed, the initial net solution is fine-tuned by means of reducing the BS discharged power (lines 21–25 in Phase 2 of Algorithm 1). When a user's route loss exceeds the maximum permissible path loss, the stopping condition is achieved. Reducing radiated power will improve spectrum re-use, lessen exposure, and save power consumption.

Algorithm 1's Phase 2, lines 26 and 27, will create the network solutions after calculating the white space availability (W_a). Take note that there has to be a high enough user density per region to ensure that, after a sufficient number of simulations, the network KPIs' progressive average converges with a low standard deviation (<3%).

2.6 Assessment situation and preliminary configuration:

In a real-life wireless suburbia situation, optimised and modelled a Cognitive Radio network to verify the suggested architecture. For both the initial green field design and the subsequent network dynamic optimisation, take India's city 68 km² into account.

As a point of comparison, researcher also simulate a classic Cognitive Radio network architecture. The implementation of the sleep mode is not feasible for this network. Because the BS disables spectrum management and user monitoring during sleep mode, this is the result. Cognitive Radio BS can be set only to idle unless there is a centralised access controller that can take over spectrum management and tracking responsibilities. When not in use, BSs carry out the vast majority of sensing, signalling, and tracking operations, but they do not process any user data payload communication.

Considering the Cognitive Radio BSs, researcher looked at 46 potential sites. Following the first optimisation, the method finds the minimal numeral of BSs needed to achieve the required coverage (NBS, refer Section 2.5) by retrieving a histogram of the ideal BSs placements. With this network topology, we can provide 94% cell-edge coverage 98% of the time.

At the height of traffic, we assume 225 users connected at once at a bit rate of 2 Mbps for each user. The models provide for three possible densities of base station infrastructure (BS), with the networks being dynamically optimised for NBS (the least number of BSs to satisfy the coverage requirement),

26%, and 51% densities, respectively. The user's connection histogram is always used for setting BSs in green field network planning.

The program will come up with two network choices for every BS infrastructure available to account for the interference limits of -116 dBm and -93 dBm in the identified Cognitive Radio signals. The -116 dBm cutoff is used to find out if a channel is occupied by finding the beacon and sense mode 0. The standard says that a cutoff of -93 dBm is needed to pick up mode zero and WRAN. There is no suggested setting for the interference level for DVB-T/T2 if concerns digital TV broadcasts. An interference restriction of -95 dBm is taken into account when assessing the re-usability of frequency that are in use by adjacent television broadcasting stations. The broadcast transmitter's suggested protective contour is the basis for this value. To safeguard the main service from detrimental interference, the selected interference limitation ensures the minimal carrier-to-interference-ratio.

The model takes into consideration the degrees of interference from the various broadcast transmitters located across the city. Researchers take into account the real transmitter designs and the ITU route loss model when calculating the path loss for TV towers in other city. Researchers think of using a one-slope experimental route loss model based on a massive UHF measurement program for path loss estimates in urban areas. When compared to the other city model, this one has better accuracy.

3. Results and Discussion:

To meet the geographical and temporal coverage requirements for the Cognitive Radio networks, minimum of 23 base stations (BSs) is required. Following the computation of the histogram (see to Section 2.5), the second optimisation phase is carried out for the 23 BSs that were selected. With a 26% (29 BSs) and 51% (34 BSs) greater BS infrastructure, respectively, the dynamic network optimisation from Phase 3 can be achieved (BS selection is made on histogram).

3.1 Pareto Efficiency:

Figure 3 illustrates the results of the objective optimisation for a) 23 base stations (minimum required to meet coverage standards, NBS), b) 29 base stations (a 26% increase in base station sites), and c) 34 base stations (a 51% increase in base station locations), under the constraint of an Interference Signal Level (ISL) of -93 dBm.

3.2 Pareto Optimality:

Figure 3 depicts the outcomes from the objective optimisation for a) 23 base stations (the minimum necessary to fulfil coverage criteria, NBS), b) 29 base stations (a 26% augmentation in base station sites), and c) 34 base stations (a 51% escalation in base station locations), constrained by an Interference Signal Level (ISL) of -93 dBm.

When compared to a density of 23 BS (Fig. 3a), an increase of 51% (Fig. 3c) decreases exposure by 15.9% (see marker 4), and spectrum utilisation by 5.7% (see marker 3). In this instance, the decrease in radiated power per BS is insufficient to offset the increase in radiating sources, so the exposure is comparable for 29 BS and 34 BS. There is a negative impact on network power consumption from the enhancements to spectrum utilisation and exposure. With a 26% increase in BS density, power consumption rises from 13.4% to 16% (Fig. 3b marking 3 and 4), and with a 51% increase in BS

density, power consumption rises by 17.8% to 20.7% (Fig. 3c). Figure 3b and 3c show network solutions with a higher concentration of functional BSs, which directly causes this.

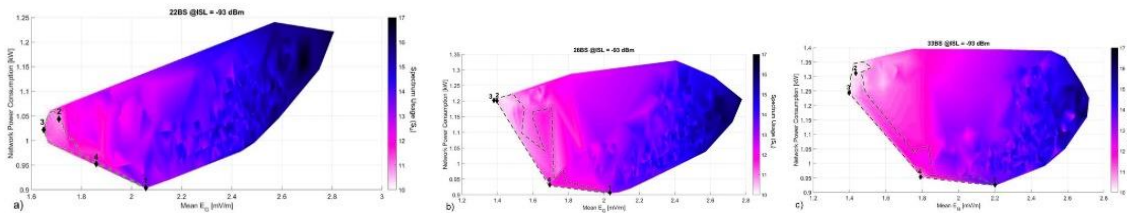


Figure 3 depicts the outcomes from the objective optimisation.

Figure 3: At ISL = -93 dBm, the optimisation outcomes for a) 22 BS, b) 28 BS, and c) 33 BS sites were found. The dashed line shows the Pareto front in part. Marker 1 shows the optimum results for power use, marker 2 shows the optimum results for spectrum usage, marker 3 shows the optimum results for exposure, and marker 4 shows optimum results for trade-off.

Regarding the most energy-efficient network setup (see Fig. 3 marking 1), this KPI doesn't change much as the number of possible BS sites rises. The change in network power use is less than the standard range, at 0.93 kW. The reason for this is that the program puts the majority of these BSs to snooze and boosts the power to extend to people far away. When the emitted power goes up, the smaller number of active BS (serving user traffic) means that less power is used. It takes 31% to 36% less power to run the network when fewer active BSs are present, but the spectrum grows by about 21% and the exposure rises from 21% to 38% (see marker 1 in Fig. 3).

Marker 4 stands for the KPI with the most fair trade-off. The median point in the Pareto boundary (marker 4) doesn't get much better when the number of BS sites is increased. When the BS density goes up by 26% (see Fig. 3b point 4), the average spectrum use only goes up by 3.4% and the world exposure only goes up by 8.7%. At the same time, the network power consumption stays about the same (the difference is less compared to standard deviation). When the BS density is 51% higher (see Fig. 3c point 4), the average spectrum use goes up by 11%, but the world exposure only goes up by 3.8%, and the network power use stays about the same.

Some places in the Pareto front (the area inside the dotted line) get better bandwidth and network exposure as the number of active BSs goes up, but this comes at the cost of using more power. In fact, the methods for optimising sunlight and power use are at odds with each other. The program makes more active BSs with low emitted power so that there is less world exposure. So that less power is used, the program causes fewer BS to be active. The reason is because the BS only uses 9W of power when it is in sleep mode, which is 14% of its highest power use. In this way, putting BSs into sleep mode leads to a better optimisation with respect to of power use. Lower emitted signal level indicates less spectrum use, but at additional even rate than with network exposure optimisation. This will help make the spectrum more useful again. It happens because the ISL limit changes the choices about connections and the distribution of bandwidth in a different way.

3.2 Cloud-based vs conventional network architecture:

A comparison of the cloud-based design with the conventional distributed architecture for 23 BS is shown in Figure 4, with percentages representing the difference for each pareto point.

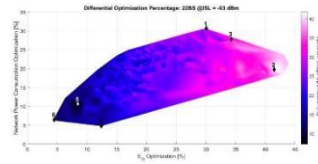


Figure 4: shows the architectural model for 23 BS

The results of net model of classic Cognitive Radio network & 23 BS showed that the network used 18.3 channels on average, had a universal exposure of 2.8 mV/m, & used 1.4 kW of power. With each Pareto point of optimised cloud based Cognitive Radio net shown in Fig. 4, researcher can see how high these values are.

By using the cloud-based design, power usage may be reduced for about 30.7%, reaching an all-time low (refer to marker 1 in Fig. 4). In this scenario, when contrasted with the conventional Cognitive Radio network design, spectrum use is 28.2% less & mean universal exposure equals 30.2% less. Increased efficiency by 41.7% (for both KPIs) and decreased power usage by 19.8% are the results of optimal trade-off between spectrum utilisation & average global exposure (look on to marker 2 Fig. 4). Reducing spectrum utilisation by 34.6%, universal exposure by 34.3%, & networks power usage for about 27.6% is the best-balanced net solution in each KPIs (consider marker 3 of Fig. 4). Figure 4 shows the conventional Cognitive Radio network consuming 4.9% more power than the proposed architecture under worst-case conditions. Figure 5 shows that the proposed architecture outperforms the conventional network by 4.4% for universal exposure, 7.4% for spectrum usage, and 4.9% for net power use. This is because, as opposed to making a local choice created only on the devices data in the BS's area, a centralised access controller can evaluate all devices' data and make a better connection decision.

3.3 Impact of ISL constraint:

For 23 BS (minimum to ensure coverage requirements), the Pareto multi-objective optimisation results are shown in Fig. 5. The interference signal level constraint is -117 dBm, which is 24 dB lower than the previous value of -94 dBm.

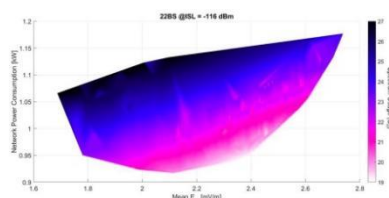


Figure 5: shows the optimisation results for 23 BS (minimum to ensure coverage requirements), the Pareto multi-objective.

If you set an interference level at -94 dBm, the outcomes for optimising network power use & world networks exposure are like to those of ISL = -94 dBm (see Fig. 5a for full details). There is, however,

a lot more use of the range. The SU value of 19.1 is the best network option for using bandwidth. The optimal spectrum usage outcomes for 23 BSs & ISL = -94 dBm are 43.8% better than this number, and the worst spectrum utilisation outcomes for 23 BSs & ISL = -94 dBm are 11% not as good. There is a 24 dB tighter ISL limit that means increasing the quantity of working BSs and lowering the signal level generated by each BS will not be enough to allow for high spectrum reuse.

3.4 Availability of White Space:

For the traditional Cognitive Radio networks in 23 BS and non-coordinated spectrum administration (Fig. 6a), the cloud-based centralised spectrum administration using 23 BS (Fig. 6b), and the same network architecture using 34 BS (Fig. 6c), the white space dispersal map is shown in Fig. 6. This map indicates the availability of white space at every grid point in the area, as described in the metric in Section 2.4.

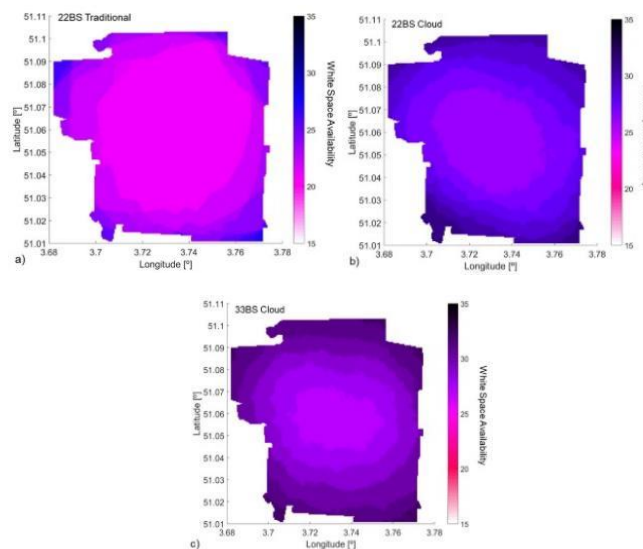


Figure 6: Shows the white space map.

The ideal outcomes in terms of spectrum use are shown in Fig. 6b and Fig. 6c, which are the white space distribution maps (marked in marker 2 in Fig. 3a with 3c, respectively). The optimised suggested architecture has 26.4% more white space availability than the usual Cognitive Radio network (Fig. 6b and 7a, respectively). This is based on the average value for the whole area. But the increase is a little less (22.8%) for the balanced optimality. For example, in the city centre, there may be a bigger difference in the amount of empty room. Because of how the BSs are spread out and how radiation from more of them mixes, the impact level gets higher at the city centre.

However, a gradient of white space accessibility is greater at 34 BS compared to 23 BS (Fig. 6b and 6c, respectively), even though the mean white space availability doesn't change much as the number of BS infrastructures that are available goes up (51% more BS infrastructures that are available). According to this, there will be more routes in an area near the city if 34 BS sites are used instead of 23 BS for planning the green field network. That's because there are more active BSs that radiate, but each one gives off less radiation. Because of path loss in the surroundings, radiation is accumulated at small area.

4. Conclusions:

Researcher found out how much better cloud-based network management for Cognitive Radio technology compared to standard distributed design by with a new multi-objective optimisation method for Cognitive Radio networks. To figure out the trade-off between three KPIs, a Pareto efficiency modelling is used.

The suggested design and optimisation algorithm decrease networks power usage for about 27.6%, mean worldwide revelation by 34.4%, & spectrum utilisation for 34.6% compared to a conventional Cognitive Radio network, achieving an optimal balance among the three key performance indicators. It is crucial to observe that even at the least favourable Pareto point, the method outperforms the conventional design by 4.9% for network power usage, 7.4% for spectrum utilisation, & 4.4% for overall exposure.

Increasing the density of the BS infrastructure in a cloud-based architecture beyond what is necessary to provide the desired geographical and temporal coverage may boost spectrum utilisation by 5.7% and worldwide exposure by 16.4%, but it comes at the cost of 13.4% to 20.7% more power consumed by the network.

Experiments will be used to study how the data rate changes with interference so that Cognitive Radio networks can get a better idea of how to deal with dynamic interference constraints.

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