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Resource Optimization in H-CRN with Supervised Learning Based Spectrum Prediction Technique

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ABSTRACT- Cognitive radio network shows potential means of granting intensifying demand for wireless applications. In this model, an efficient resource optimization scheme with Priority Pricing Technique (PPT) is proposed with supervised learning-based SVM to tackle limited spectrum availability and underutilization in Hybrid-Cognitive Radio Networks (H-CRN). H-CRN works under the principle of detection of PUs states (active/inactive). If spectrum sensing is made in favor of active PUs, then the CSI (Channel State Information) is estimated and works in underlay principle. If it is made in favor of inactive PUs, then the transmission is performed in overlay manner. In the proposed PPT the PUs and SUs with highest channel gain have the highest priority to use the spectral resources. SVM is used as an effective technique of spectrum sensing to provide higher probability of detection of PUs as soon as possible. The proposed method faces following challenges such as in order to enhance the CRN transmission performance, the PUs have to withstand more interference power and transmit power control is needed in improving the sum rates when the interference is severe in H-CRN. With Simulation outcomes, the assessment of the proposed (PPT) model among (Fixed Pricing Technique and Without Pricing Technique) indicates the proposed method's improved efficiency. The results reveal significant effectiveness in obtaining better classification accuracy with less computation complexity, increased throughput, spectral efficiency and energy efficiency of the network.

Keywords: H-CRN, SVM, Spectrum Prediction, Resource optimization, PPT.

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1. INTRODUCTION

Today's growing demand for wireless applications, spectral efficiency is the foremost challenge as many users are to be found widely throughout the network [1]. Spectrum scarcity issues have been an alarm for wireless applications since their origin. The Cognitive Radio (CR) technology is raised as a potential remedy for shortages of spectrum-by-spectrum detection with fast response time at low and high Signal-to-Noise Ratios (SNR) regions [2].

An example of H-CRN is shown in *figure 1* by combining both overlay and underlay in which the former case is: Secondary Users (SUs) access the spectrum only when PUs absence occurs, while the latter case is SU and Primary Users (PUs) cooperate under SINR condition in the same available channel. The dotted circle denotes the active state of PUs and the circles denotes the inactive state of the PUs.

Effective usage of Under-utilized spectral resources is a challenging task to boost network existence, with increased throughput, minimum computational delay and control overheads. In hybrid CRN, efficient resource management involves spectrum prediction, scheduling and allocation. In this model, SVM-based supervised machine learning with Priority Pricing Technique (PPT) is used for effective resource allocation.

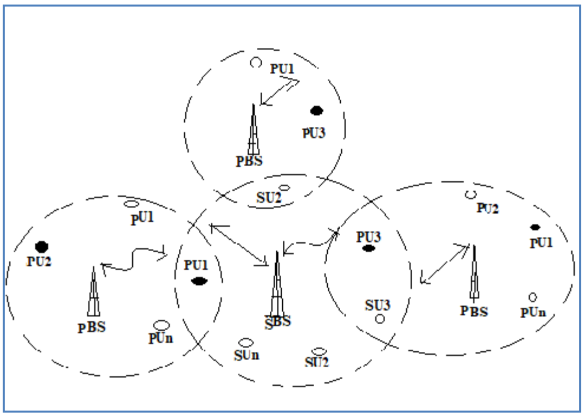

Figure.1 Hybrid-Cognitive Radio Network

Machine learning-enabled spectrum sensing achieves an optimized detection margin with a better probability of detection in comparison with conventional spectrum sensing techniques. Conventional sensing methods create overhead in sensing cooperation which leads to higher energy consumption during sensing and it consumes more sensing time [3,4]. A novel machine learning-enabled sensing achieves cooperative gain with considerable limits in cooperative overhead. The SVM classifier classifies the received energy vector from PUs into 'spectrum hole available or unavailable'. The training phase of this classifier involves learning from training feature vectors that are taken from the PUs.

With the spectrum prediction method, the licensed and unlicensed user collisions can be minimized by identifying the best possible spectrum holes and allocating the best channels to the cognitive users. The SUs are allowed to access the white hole only when it is noted to be free. The proposed SVM model is useful in analysing the spectrum hole with good classification accuracy and in allocating the users to the best possible spectrum hole.

2. ASSOCIATED WORKS

Spectrum Sensing proposed in [5], is done in an IoT cognitive network based on an SVM classifier to enhance the network performance, which in turn amplifies the utilization of resources. Authors in [6], investigated various machine learning-enabled spectrum sensing methods in CRN. The method in [7], uses several learning-based spectrums sensing for real signals for PU detection. It was observed that performance is better for SVM and K-nearest neighbour compared to decision trees. Power and channel allocation are done in [8], with optimization problems by SVM technique and particle swarm optimization with enhanced primary capacity. SVM classifier considering various hypotheses for spectrum classification shows better efficiency in sensing the spectrum done in CR communication as proposed in [9]. SVM, Naïve Bayes and Multilayer preceptor are compared in [10], with the traditional CSS method.

A power algorithm in 5G-CRN using game theory was proposed by authors in reference [11, 12]. It derives the utility function for licensed and unlicensed users without a pricing method hence it does not provide efficiency of the network. As in [13], fair sub-carrier allocation and power assigning are based on cooperative games in the NOMA multi-carrier network. In this model, the interference constraints are not used for resource allocation which leads to inefficiency in the suggested method in real-time applications. In an underlay cognitive NOMA network, the pricing mechanism with game theory was employed for power allocation in [14]. Herein fixed pricing function was used which makes the interference management inflexible and thus directly impacts the network function. The pricing scheme in [15], uses the Stackelberg game for allocating the spectrum by making interaction with primary and secondary users making the primary user as leader and SU as follower. This method does not consider the interference occurrence during data transmission. Authors in [16,17], proposed a coalitional game for spectrum allocation in SCMA to maximize the user's throughput. However, computational complexity is not addressed in this proposal.

3. MOTIVATION AND CONTRIBUTION

Our proposed model uses Priority Pricing Technique (PPT) dynamically based on user demands with traffic analysis largely to lessen the complexity of the computation in Hybrid-CRN by keeping the threshold power of intrusions lying on primary networks below the set value. During the process of achieving better quality of services with good spectral efficiency, numerous challenges arise. This is mainly because of capacity limitations of multiple unlicensed users. The proposed method addresses channel allocation and classification of the available spectrum hole with capacity constraints in an efficient manner. Here both spectrum prediction and allocating the predicted frequency are carried in hybrid way. The efficiency of the proposed method increases the chance of utilizing the radio frequency spectrum in tandem with increased spectral and energy efficiency in H-CRN.

The priority pricing model works on the following two constraints:
(i) Secondary user's demand for spectrum usage is given high priority based on its high transmission power and interference rate.
(ii) By selecting the perfect SUs it is possible to restrict interference from users and enable energy saving during data transmission.
(iii) Users should be free from interference from other users.

A novel method of classifying users with best energy statistics based on data samples collected from the PUs has been developed. The method leads to an optimized classification with machine learning-enabled spectrum sensing and optimization techniques that aims to increase achievable PU sensing accuracy and cooperative gain.

Firstly, the SVM spectrum prediction method Classifies the multiple users by extracting the PU features predicting the achievable spectral hole and assigning the channels to each requesting unlicensed user, secondly, the Priority Pricing Technique (PPT) enhances the utility function of both licensed and unlicensed users through good quality of service in a network by means of energy and spectral efficiency.

This research paper has been presented in six sections viz., *Section 1* deals with introduction. Associated works, Motivation and contributions are provided in *section 2*. *Section 3* presents the system model for Energy Vector Generation. *Section 4* and *section 5* comprises of Channel Allocation Mathematical model, Interference and Power Constraint Model. In section 6 Simulation results are discussed. The paper concludes with future scope and references.

4. SYSTEM MODEL FOR ENERGY VECTOR GENERATION

H-CRN consists of multiples of spatially distributed CRUs (Cognitive Radio Users). Each CRU initially performs Spectrum sensing in CRN. Spectrum sensing is a crucial fundamental component of cognitive networks that prevent unauthorized users from using licensed bandwidth. Spectrum sensing is made possible by secondary users when a primary user is present which may lead to the following testing hypothesis problem:

Hypothesis (H_0) =>> y(m) = a(m); if PU is in absence state (1)

Hypothesis (H_1) =>> y(m) = x(m)+a(m); if PU is in present state (2)

When a primary user is not present, hypothesis H_0 claims that y(m) the expected complex signal contains only noise a(m), while hypothesis H_1 states that y(m) the obtained complex signal contains primary signal x(m) contaminated by a(m). The primary objective of SVM spectrum sensing is to accurately decide upon two crucial probabilities, Pd and Pf using extracted PUs signal features. Using a pre-filter, the noise bandwidth is filtered and the signal energy received is

$$R=\sum_{m=1}^{M} y(m)\ ; \tag{3}$$

A feature vector, which represents an estimated energy level at each cognitive device, is created from the incoming signal energy vector. The pre-determined threshold value derived from the Neyman-Pearson criterion is compared to the received signal energy.

$$R=\sum_{m=1}^{M} y(m)<\gamma_{th} \text{ PU is unavailable} \tag{4}$$

$$R=\sum_{m=1}^{M} y(m)\geq\gamma_{th} \text{ PU is available} \tag{5}$$

The effectiveness of signal energy detection is defined by p_d and p_f

$$P_d=P(R\geq\gamma_{th}/H1) \tag{6}$$

$$P_f=P(R<\gamma_{th}/H0) \tag{7}$$

The requirements of a spectrum detector are low false detection and high detection probability. An ideal balance between pd and pf should be taken into consideration while choosing the detection threshold. In practice, a particular false alarm rate determines the detection threshold. Consequently, the noise power variance is sufficient to choose the detection threshold.
Spectrum hole sensing using machine learning enables a mapping relation classifier for mapping the energy statistics at every time slot. If PU is present then it is classified as rt=1. In case PU is absent it is then represented as rt= -1. Consequently (Rt,rt) is a collection of training samples with Rt training pattern and rt binary sensing results.

Finding an ideal classification hyperplane that complies with sorting requirements is the main goal of SVM. By using this hyperplane, the sorting interval should be maximized while guaranteeing classification accuracy A classifier model coupled with (SVM and CR) decreases errors by using linearly separable vectors which are present in the network.

To train the samples, it is necessary to map the energy vectors in space by means of a nonlinear mapping function which is given below [18]. This increases the detection margin.

$$W_g * \emptyset(R^t) + B_0\ \geq 1 \text{ if t=1} \tag{8}$$

$$W_g * \emptyset(R^t) + B_0\ \leq -1 \text{if t=-1} \tag{9}$$

Where W_g acts as the weighting vector, B_(0) as bias and α as the relaxation factor which neglects collision due to noises in the classifier.

y(m) the energy vector is classified correctly on $0 \leq \alpha \leq 1$.

By classifying the samples properly by neglecting the noise impact, the classifier would ensure the condition given below

$$t\rightarrow W_g * \emptyset(R^t) + B_0\ \geq 1-\alpha^t \tag{10}$$

The optimization issue where the classifier margin must be maximized and the total number of errors must be minimized can be written as

$$min\frac{1}{2}\left|W_g\right|^2+\sum_{t=1}^{N} IF(\alpha^t\geq 1) \tag{11}$$

s.t. $W_g * \emptyset(R^t) + B_0\ \geq 1-\alpha^t$, t=1,2,…T $\alpha^t \geq 1$, t=1,2,…T

where IF is an indicator function that is (1= true values and 0= incorrect values) and $\left|W_g\right|^2$ is soft margin constant. This is the multiplier's final value with support vector K_m:

$$M(W_g,\alpha,k)=\frac{1}{2}\left|W_g\right|^2+\sum_{t=1}^{N}\alpha^t-\sum_{m=1}^{N} y(m)\emptyset K_m) \tag{12}$$

From sensed energy statistics the following features are extracted, where X_1 is ten times the signal power. X_2 is the averaged squared signal power. X_3 is the square root of the mean of signals. These features are fed into the SVM classifier for spectrum sensing classification.

$$X1=\frac{10}{N}\sum_{i=1}^{N}\rho_i \tag{13}$$

$$X2=\frac{1}{N}\sum_{i=1}^{N}\rho_i{}^2 \tag{14}$$

$$X3=\sqrt{(\sum_{i=1}^{N}\rho_i)^2} \tag{15}$$

#ALGORITHM 1
STEP1: Obtain the energy statistics of the signal.
STEP2: PU signal features are extracted from the received signal sample.
STEP3: Create an SVM classifier model
STEP4: Choosing the classification model parameters
STEP5: Initialise the training samples with weighting vectors.
STEP6: Features are mapped with suitable labels
STEP7: If features are mapped correctly
STEP8: For every SU request
"Request Count=Num of request++"
Search for BW
If BW is available
Assign SU to available BW
else
queue up the request.
If request processing<threshold
Request is responded
else
Hold the response count
End the process.

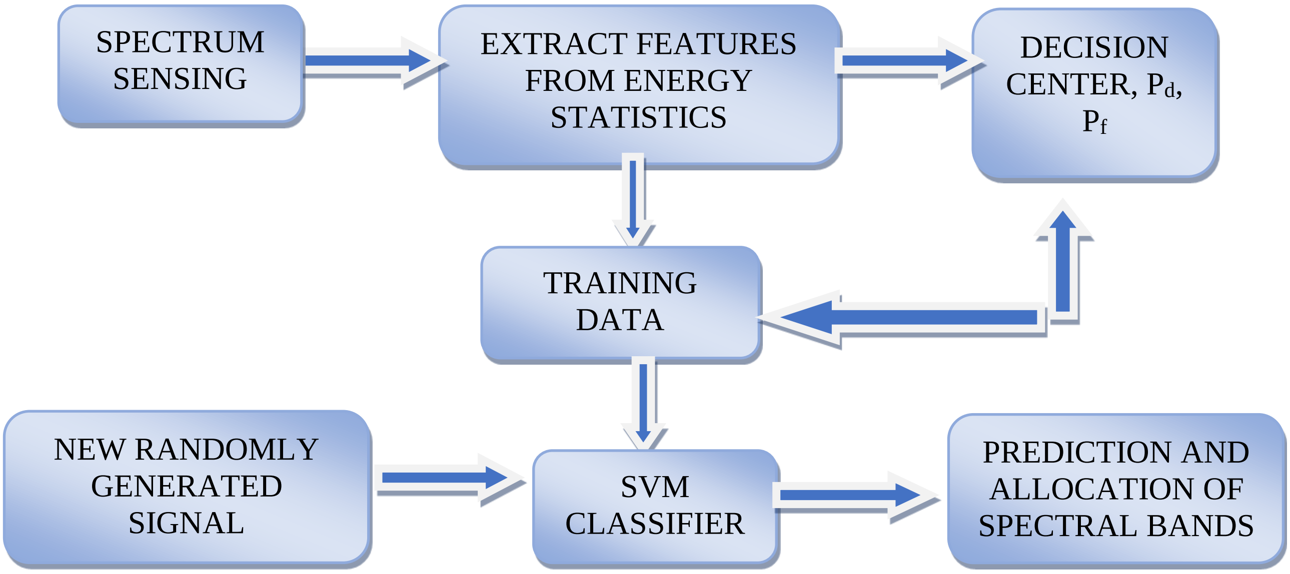

Figure .2. Flow Chart of SVM Classifier

5. CHANNEL ALLOCATION MATHEMATICAL MODEL

In the proposed methodology weighted channel assignment has been used for the cognitive users thus ensuring less primary user usage, and less congestion with other cognitive users with optimized channel capacity. The proposed method maximizes throughput, resource utilization and transmission rate.

The objective of maximizing the sum of cognitive users' throughput by optimized allocation of frequency spectrum to cognitive users with tolerable interference power is a critical issue. Let us consider the channel allocation matrix as C={$c_{x,y}$//$c_{x,y}$ ε 0,1}.where X represents cognitive users with Y number of channels. If $c_{x,y}$ =1 when user x is allocated to channel y then $c_{x,y}$ =0 is used when user x is not allocated to channel y. If the users choose the highest channel gain for a subcarrier, the data rate will be maximized.

$$UF=\sum_{x=1}^{X}\sum_{y=1}^{Y} C_{x,y} \quad (16)$$

$$C_{x,y}=1/2\,C_{x,y}B_y\log_2(1+\gamma) \quad (17)$$

$C_{x,y}$ is the cognitive user throughput with B_y as the allocated bandwidth.

The optimized channel allocation C* can be obtained from the following constraints.

$$C^*=\arg\max UF \quad (18)$$

Subjected to:

C1= $\gamma_x > \gamma_0$, x=1,2,3…X

C2= $c_{x,y}$ ε (0,1).

6. INTERFERENCE AND POWER CONSTRAINT MODEL

Priority pricing method is employed to enhance the network performance by limiting the interference generated between the users. The power and interference constraints are then as follows. It is highly essential that the interference model in a CRN is given importance as interference between various users including primary and secondary users in a network; will lead to degradation in the network performance.

A good QoS for all the users in a network can be ensured by adjusting the interference range using the adjacent channels and by defining a certain interference threshold (interference range< interference threshold). This is derived mathematically by using the equations given below.

From the (PSD) power spectral density the interference on primary and secondary users is derived as follows;

$$S_l(f)=P_l*T*Sinc(fT) \quad (19)$$

Where $S_l(f)$ is the PSD function, P_l is the power generated by the l^{th} subcarrier in the network.

In *equation (2)* I_{PU}^{SU-l} mentions the interference from secondary users to primary users on the lth subcarrier. d_{PU-l} is a distance of primary users to the lth subcarrier. Similarly, interference generated by primary users on secondary is shown in *equation (21)*

$$I_{pu}^{su-l}(d_{pu-l}, P_l) = \int_{d_l-B/2}^{d_l+B/2}\left|g_{1_{su-PU-l}}\right|^2 * P_l*T*Sinc(fT)df$$
$$=\int_{d_l-B/2}^{d_l+B/2}\left|g_{1_{su-PU-l}}\right|^2 * S_l(f)df \quad (20)$$

$$I_{su}^{pu-l}(d_{su-l}, P_l) = \int_{d_l-B/2}^{d_l+B/2}\left|g_{2_{pu-su-l}}\right|^2 * P_l*T*Sinc(fT)df$$

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$$=\int_{d_l-B/2}^{d_l+B/2}\left|g_{2_{pu-su-l}}\right|^2 * S_l(f)df \quad (21)$$

$$\sum_{l=1}^{L}\sum_{su=1}^{M} C_{su-l}\, P_l^M \theta_l^{pu} \le I^{TH}, \forall pu \in \{1,2,3 \dots pu\} \quad (22)$$

Where I^{TH} is the interference level threshold, C_{su-l} is the channel occupancy indicator. i.e

$$C_{su-l} = \begin{Bmatrix} 1, \text{if channel assigned to Mth secondary use} \\ 0, \text{means channel is busy} \end{Bmatrix}$$

The maximum power budget (P_{MAX}) defines the power constraint on the network as given in *equation (5).*

$$P_{MAX} \ge \sum_{l=1}^{L}\sum_{su=1}^{M} P_l^M * C_{su-l} \quad (23)$$

P_l^M, power of M^{th} SU on l^{th} subcarrier.

$$\gamma_l^M = \frac{P_l^M |h_{l,M}|^2}{\delta_{AWGN}+\sum_{pu=1}^{N} I_{pu,l}^M} = \frac{P_l^M |h_{l,M}|^2}{I^{TOT}} \quad (24)$$

Where $I_{pu,l}^M$ is interference from primary users to M secondary users on the l sub-carrier.

The optimized power allocation with pricing factor and interference factor are given below by adopting the Lagrangian multipliers.

$$P_l^* = \left[\frac{1}{\lambda+\sum_{l=1}^{L}\theta_l^{pu}\pi_{su}} - \frac{I^{TH}}{|ho|^2}\right]^+ \quad (25)$$

$$P_l^* = \sum_{l=1}^{L} log_2\left(1+\frac{P_{l|ho|^2}}{I^{TH}}\right) - P_l\sum_{l=1}^{L}\theta_l^{pu}\pi_{su} - \lambda\left(\sum_{l=1}^{L}P_l - P^{MAX}\right) + \sum_{l=1}^{L}P_l\beta$$

Differentiate the above and equate to 0 with respect to P_l^*

$$\frac{\partial\tau}{\partial P_l^*} = \left(\frac{I^{TH}}{P_{l|ho|^2}+I^{TH}}\right) * \frac{|ho|^2 I^{TH}}{(I^{TH})^2} - \lambda + \beta - \sum_{l=1}^{L}\theta_l^{pu}\pi_{su} = 0$$

The karush Kuhn tucker condition is stated as:

$P_l^* \ge P^{MIN}$;$\beta \ge 0$;

$$\lambda \ge 0, \lambda\left(\sum_{l=1}^{L}P_l - P^{MAX}\right) = 0$$

$P_l\beta = 0, \forall l \in \{1,2,3 \dots L\}$

Where λ , β are non-negative legrangian multipliers

$$P_l^* = \frac{1}{\sum_{l=1}^{L}\theta_l^{pu}\pi_{su}+\lambda-\beta} - \frac{I^{TH}}{|ho|^2} \quad (26)$$

Since$P_l^* \ge P^{MIN}$, $P^{MIN} = 0$

$$\frac{I^{TH}}{|ho|^2} \le \frac{1}{\lambda+\sum_{l=1}^{L}\theta_l^{pu}\pi_{su}-\beta};$$

If $\frac{I^{TH}}{|ho|^2} < \frac{1}{\lambda+\sum_{l=1}^{L}\theta_l^{pu}\pi_{su}}$,then $\beta = 0$

$\beta P_l^* = 0$, $\beta \ge 0$, P_l^*=0 is attained.

$$P_l^* = \frac{1}{\sum_{l=1}^{L}\theta_l^{pu}\pi_{su}+\lambda} - \frac{I^{TH}}{|ho|^2} \quad (27)$$

The above equation defines the optimal power allocation

The priority pricing model considers the Secondary user's demand for spectrum usage by giving high priority based on its high transmission power and interference rate. let us consider different users with different transmit power, the user with high transmit power is given higher priority than the other users to ensure the interference-free transmission.

$(P1, P2, P3 \dots P_N)=\max(P_i)$ (28)

By the priority pricing function, the interference that occurs during data transmission with licensed primary users can be controlled. It defines a certain limit to an allowable intrusion to PUs.

$$\sum_{l=1}^{L}\theta_l^{pu} \le I^{TH} \quad (29)$$

Maximizing Transmission Rate (TR) of users in a network is given below as an optimization problem with the following constraints: the transmission rate obtained from the M^{th} secondary user on the lth subcarrier is;

$$TR_l^M = \Delta f log_2(1+\gamma_l^M) \quad (30)$$

Objective: maximum (TR_l^M)

Subject to: $\{C1: C_{su-l} \in \{1,0\}, \forall l, su$
$C2: \sum_{su=1}^{M} C_{su-l} \le 1, \forall l$
$C3: \sum_{l=1}^{L}\sum_{su=1}^{M} C_{su-l}\, P_l^M\theta_l^{pu} \le I^{TH}, \forall pu \in \{1,2,3 \dots pu$
$C4: P_{MAX} \ge \sum_{l=1}^{L}\sum_{su=1}^{M} P_l^M * C_{su-l}$
$C5: P_l^M \ge P_{MIN}$

The power assigned by subcarriers occurs in the network between P_{MIN} &P_{MAX} .

C1 is the channel allocation to secondary users on l subcarriers; in C2 each secondary user can occupy only one subcarrier. C3. is the interference threshold limit. C4. is maximum power transmission. C5. is the minimum power for secondary user's transmission.

The objective of utility maximization of network users both PU and SU, it has been assumed that the licensed users will price the secondary user interference in order to share the spectral hole with SUs. The Stackelberg game is used to analyze the PU interaction with SU, where PU is a leader and SU is a follower. Leader mentions the transmit power of PUs, allocation time and the SU interference level pricing. And follower mentions the power of SUs. By implementing the Stackelberg game method, it is possible to assign optimal interference level pricing and transmit power allocation of the secondary users.

Let the utility function of users incorporate a pricing scheme to enhance the network function.

Let the licensed primary user assign a price for interference from unlicensed users, the primary user utility function is

$$U_{PU} = log_2\left(1+\frac{P_{pu}h_0}{\sigma^2}\right)\delta + \sum_{su=1}^{M} P_{su}w_{su}\pi_{su} \quad (31)$$

Where π_{su} is the interference price of the secondary user with PU utility factor with unit rate δ

The interference generated is controlled by this pricing factor π_{su}

The utility function of M secondary users is

$$U_{SU}^{M} = \frac{log_2\left(1+\frac{P_{su}h_{su}}{\sigma^2}\right)\delta - P_{su}w_{su}\pi_{su}}{P_{su}+P_c} \quad (32)$$

P_c is the added power consumption during data transmission.

the utility function of primary users is maximized by considering the interference energy price (π_{su}) with optimized transmit power (P_{pu}) in each data transmission and the utility function of secondary users is improved with transmit power for data transmission.

(OP1): max U_{SU}^{M}

s.t. $P_{su} \geq 0$.
(OP2): max U_{PU}

s.t. $P_{pu} \geq 0$, $\pi_{su} \geq 0$

(OP.3): maxπ_{su} $\sum_{su=1}^{M} P_{su}w_{su}\pi_{su}$

$$\frac{\partial o_\pi}{\partial \pi_{su}} = w_{su}\left(\frac{\partial P_{su}}{\partial \pi_{su}}\pi_{su} + P_{su}\right) = 0$$

Let π_{su} denotes the optimal interference level price, o_π is the optimization function (2).

$$\pi_{su} = -\frac{P_{su}}{\frac{\partial P_{su}}{\partial \pi_{su}}}$$

To get π_{su} ,PU should know the transmit power of secondary users and $\frac{\partial P_{su}}{\partial \pi_{su}}$;

$$\pi_{su} = S(\pi_{su}) \quad (33)$$

Where $\pi_{su} = \{\pi_{su1,su2,\ldots M}\}$
$S(\pi_{su}) = \{S(\pi_{su1,}) \ldots . S(\pi_{suM,})\}$
Which denotes the interference price for SU.

#Algorithm2: Algorithm for Priority Pricing Technique

Start
Step 1: initialize the parameters: P^{MAX}, P^{MIN}, I^{TH}, θ_l^{pu},L,M
Step 2: set the initial channel parameter as $C_{su-l} = 0\ \forall i, su$
Step 3: Assign π_{su} with respect to the interference constrains
Step 4: find the optimal power by pricing equation
Step 5: calculate the channel gain:
$h_l = \sum_{su=1}^{M} C_{su-l} * hsu, l$
Step 6: for channel allocation:
For l=1 to L do
su= argmax$\{h_{su,l}\}$; $C_{su-l} = 1$
Step 7: Allocate the spectrum
End

7. SIMULATION RESULTS

To evaluate the proposed method MATLAB is employed for resource optimization in H-CRN with a Supervised Learning Based Spectrum Prediction Technique. The channel capacity in relation to the interference threshold, energy and sum spectral efficiency, and sensing accuracy in predicting the spectrum holes are the performance measures employed in this study. The simulation parameters used are shown below. The training dataset comprises 1000 energy test data samples. It is tunned from (-30dB - 0dB) SINR values. With sensed signal energy level, the transmit power of SUs is varied.

Table 1: Simulation Parameters

Simulation parameters	values
Total bandwidth	5MHz
Transmitter power	40(dBm)10w
Noise power density	-174 dBm/Hz
No. of PUs	10
No. of SUs	45
Channel	AWGN
Interference threshold	1 mW

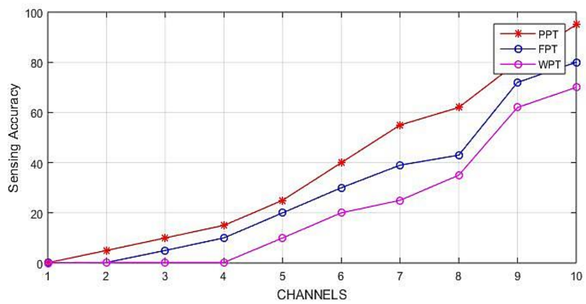

Figure.3. Sensing accuracy vs No. of channels

In *figure 3*. We obtained the sensing accuracy for a number of channels. As the number of channels increases the sensing accuracy of PUs increases for the PPT which is due to the dependency of channel states. To obtain good detection probability the SU has to sense large amount of signal samples. Our proposed Priority Pricing Technique (PPT) compared with the existing Fixed Pricing Technique (FPT) and Without Pricing technique (WPT) obtains good sensing accuracy of 91.2 using the SVM classification method.

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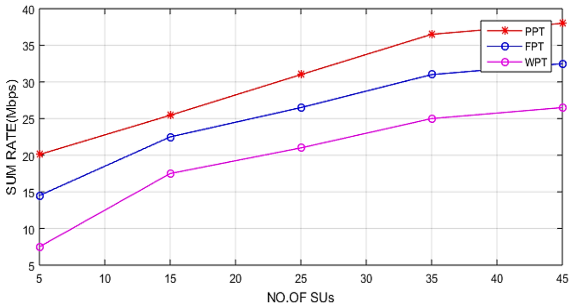

Figure 4. Sum Rate vs SUs

In *figure.4* system sum rate is presented for proposed and existing methods which shows that as the number of secondary users increases for accessing the under-utilized spectrum the total sum rate of the H-CRN goes on increasing and the proposed PPT achieves a sum rate of 37.5 Mbps/Hz than the existing FPT with 31.21 Mbps/Hz and WPT with 25.04 Mbps/Hz for transmission power of 30 dBm. The proposed PPT method achieves a higher sum rate than the FPT and WPT methods due to the dependability of channel gains in allocating the transmission power to secondary users which was not considered in FPT and WPT.

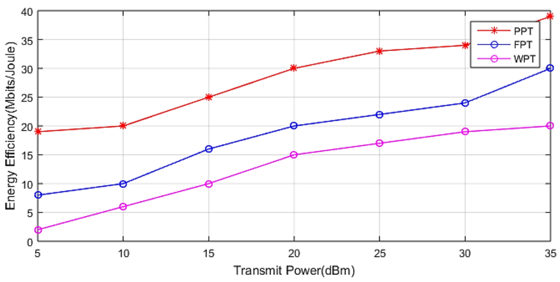

Figure 5. Energy Efficiency Vs Transmit power

Figure.5 illustrates energy efficiency for the proposed Priority Pricing Technique. Here the transmit power control plans an important role in enhancing the energy efficiency of the system. If the SUs is operating in overlay case high transmit power is used to improve the rates, if it works in underlay case less transmit power is used to avoid interference to PUs. In FPT, on basis of fixed ratio transmit power is assigned to all users and it is inefficient due to inconsideration of users' channel condition in determining the power level. WPT is inefficient because it generates interference to PUs without any CSI and assigning the same power level and hence the proposed PPT performs better than FTP and WPT due to the dependability of channel gains in allocation of transmit power to SUs. A higher efficiency of 39.8 Mbits/Joule than the FPT with 30.24 Mbits/Joule and WPT with 20 Mbits/Joule is obtained with 30 dBm broadcast power. The proposed technique achieves superior energy efficiency than the previous methods with enhanced SINR and throughput.

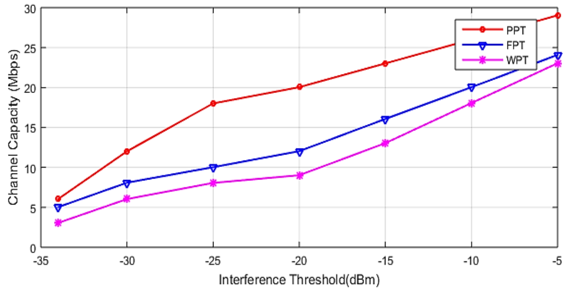

Figure 6. Channel capacity vs Interference threshold

In *figure 6*. The channel's capacity versus the primary user's maximum permissible interference level for the proposed PPT, and existing FPT and WPT methods are displayed. It is observed that for a -5 dBm interference threshold level. Our proposed PPT obtains a higher channel capacity of 29.8 Mbps/Hz comparing the existing FPT by 24.31 Mbps/Hz and WPT by 23.02 Mbps/Hz. To enhance the transmission performance, the PUs has to endure more interference power. As the interference threshold level is higher the capacity of the channel is higher.

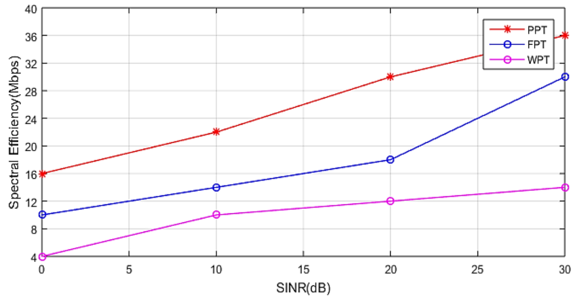

Figure 7. Spectral Efficiency vs SINR

Figure.7 illustrates spectral efficiency vs. SINR of the proposed PPT and the existing FPT and WPT. With the increased SINR the proposed PPT achieves good performance than the existing methods because of the channel state estimation. The FPT and WPT are inefficient due to the ignorance of CSI of PUs and SUs. Here the PPT achieves 36 Mbps/Hz of efficient spectrum compared with existing by 30.2Mbps/Hz for FPT and 14.12 Mbps/Hz for WPT. So PPT for resource optimization is a suitable technique for enhancing the next-generation wireless communications network performance. Comparative Analysis of the results is given in *table.2* From this analysis the proposed Priority Pricing Technique achieves better performance than the existing methods. The proposed PPT method achieves a higher sum rate, Energy efficiency and spectral efficiency than the FPT and WPT methods due to the dependability of channel gains in allocating the transmission power to secondary users which was not considered in FPT and WPT.

Table .2 Comparative Analysis of the results

Metrics	PPT	FPT	WPT
Sensing Accuracy	91.2	80	70.01
Sum Rate (Mbps)	37.5	31.21	25.04
Energy Efficiency (Mbits/Joule)	39.8	30.24	20
Channel Capacity (Mbps)	29.8	24.31	23.02
Spectral Efficiency (Mbps)	36	30.2	14.12

8. CONCLUSION

An efficient resource optimization scheme with Priority Pricing Technique (PPT) is proposed with supervised learning-based SVM, to tackle limited spectrum availability and underutilization in (H-CRN). The proposed method addresses channel allocation and classification of the available spectrum hole with capacity constraints in an efficient manner. The efficiency of the proposed method describes increasing the chance of utilizing the radio frequency spectrum with increased spectral and energy efficiency of 36 Mbps and 39.8 Mbits/Joule in an H-CRN. Algorithm can achieve 91.2% detection performance at an SNR level ranging from (0-8dB) with a transmit power of 30 dBm. The upcoming future study is to compute the computational complexity of an efficient resource allocation algorithm using evolutionary learning models.

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