Defence Science Journal, Vol. 74, No. 6, November 2024, pp. 911-920, DOI : 10.14429/dsj.74.19808

Multiple Jammer Attacks on Cognitive Radio Networks over Noisy Channels: A Strategic Game with Incomplete Information

Deepak B.R.* and Dhananjay Kumar

Department of Information Technology, Madras Institute of Technology, Anna University, Chennai - 600 044, India
**E-mail: swatdk_07@yahoo.co.in*

ABSTRACT

We model the anti-jamming system for cognitive radio networks under multiple jammer attacks using game theory as incomplete information games. The game model has three players: nature (representing channel impairment), jammer, and cognitive radio with sequential moves. Typically, sequential games with incomplete information use the Perfect Bayesian equilibrium solution concept, where beliefs are determined by Bayes' rule to identify the player type. In the proposed Perfect Hidden Markov -Viterbi equilibrium solution concept, beliefs are determined by the Hidden Markov Model - Viterbi decoding instead of Bayes' rule to identify the jammer type. A general form of expression is derived to compute players' payoff for probability-based belief systems to find equilibrium in anti-jamming games with incomplete information under multiple jammer attacks.The simulation results show that over time, with a gradual reduction in the bit error rate at the receiver without any channel coding for Binary Phase Shift Keying (BPSK) modulation and in the noisy Rayleigh fading environment, the proposed Perfect Hidden Markov - Viterbi equilibrium solution concept performs better than Perfect Bayesian equilibriumby 0.8 % and the traditional pseudorandom-based frequency hopping technique by 1 % in terms of the average uncoded bit error rate.

Keywords: Anti-jamming; Cognitive radio; Game theory; Multiple jammer; Perfect bayesian equilibrium; Perfect hidden markov - viterbi equilibrium

NOMENCLATURE

ψ	: Strategic form game with incomplete information
Ω	: Type of player
S	: Pure strategies of player
H	: Player beliefs about the type of other players
P	: Payoff functionof player
λ	: Cost of the jammer for missing cognitive radio transmission
τ	: Cost of cognitive radio for transmission loss due to jamming
EU	: Expected utility of player
p	: Probability of a channel to be impaired with high noise or a deep fade event
q	: Probability of a channel being free of high noise or deep fade event
u	: Probability of the jammer being strong
v	: Probability of the jammer being weak

1. INTRODUCTION

1.1 Background

In the present threat landscape, the jamming attack on Cognitive Radio Networks (CRNs) does not need to be from a single jammer alone. An adversary may deploy multiple jammers in a radio environment to increase the probability of success and enforce an efficient communication blockade. In mobile environments, jammers are most energy-constrained as battery source powers. The jamming energy constraint makes the adversary opt for jamming techniques that are energy-efficient and accurate. The jammer, who can leverage advanced transmission detection and jamming techniques, will not spend much energy on all transmissions. This category of jammers prefers jamming precision to conserve power to last longer. The smart-hybrid jammer[1] does not transmit to block all channels but assesses the radio environment for a specific target, and it can be both reactive and proactive. When multiple jammers attack a CRN, an efficient anti-jamming mechanism is required to protect the radio transmission from a jamming attack. Even the latest 5G New Radio (NR) architecture uplink transmission can be disrupted using smart jamming attack[2] using Software Defined Radio (SDR), thereby preventing the User Equipment (UE) from communicating with the network. To counteract jamming attacks, some anti-jamming resistance methods, such as the Q-learning[3] technique, help the transmitter learn autonomously without knowing the patterns of attackers by adjusting its signal power against several jamming events. The wireless power control transmission problem under multiple jammers attacks[4] is formulated with latency as user communication utility. The optimal power control strategy in a game-theoretical scenario is designed and the equilibrium strategies are derived in closed form. The optimal power control framework[5] proves that when multiple equilibria arise, the player has the same payoff for each,reflecting the communication's stability. The Nash and Stackelberg equilibrium was derived in closed form for the multi-jammer power control-SINR game.

Received : 08 January 2024, Revised : 25 August 2024
Accepted : 05 September 2024, Online published : 25 November 2024

The problem of resource assignment in a communication system under uncertainty on the jammer's channel was investigated using a Bayesian jamming game framework[6] with throughput as user utility. The Nash strategy was more sensitive to varying a priori probability than the Stackelberg strategy. The anti-jamming solution[7] proposed for securing 5G and 6G wireless communication in urban environments uses the Reinforcement Learning-based technique called Deep Deterministic Policy Gradient (DDPG) for UAV-mounted Intelligent Reflecting Surfaces (IRS), to optimize trajectory and phase shift beam forming for mitigating the effects of multiple jammer attacks. Type uncertainty[8] can be used to mitigate the jamming attack, and the probability distribution of other users' system parameters, such as energy cost and physical channel, is characterised as beliefs in the Bayesian game theoretical model. Additionally, the strategy of hiding their type prevents adversaries from clearly distinguishing the node as a transmitter or jammer is found to be a defence mechanism affecting the jammers' efficacy.

Channel state estimation is one of the essential operations for building an efficient anti-jamming solution. Assumptions, such as jammers being uncooperative, immobile and CRNs having perfect channel state information, are found in some simulation-based studies. However, it is highly improbable that Cognitive Radio (CR) nodes will have perfect channel state information in real-world conditions. Accessing the relationship between jammers is also very difficult, and making assumptions about the jammer being immobile is too restrictive. Therefore, we are not making those assumptions. All our adversaries are smart-hybrid jammers with reactive and proactive capabilities. Since it is a mobile environment where CR nodes and jammers often move, the only known limitation of the jammer in our simulations is that jammers are battery-powered and energy-constrained, similar to CR nodes.

1.2 Contribution

We propose an anti-jamming system for CR networks using the novel Perfect Hidden Markov - Viterbi equilibrium solution concept, which helps in smart channel selection for CR transmission to evade and survive the energy-constrained multiplayer radio jamming attack. Though the Hidden Markov Model[9] and Viterbi decoding algorithm[10] were used to build anti-jamming solutions such as jamming detection[11] and to counteract single jammer attacks[12], our approach has integrated it with game theory to create a new solution concept called the Perfect Hidden Markov- Viterbi equilibrium to identify the equilibrium in the anti-jamming games with incomplete information under multiple jammer attack. The proposed technique shows a lower Bit Error Rate (BER) than the existing Perfect Bayesian Equilibrium (PBE) solution concept traditionally used for games with incomplete information and the pseudorandom frequency hopping technique based on the Mersenne Twister algorithm[13]. A general form of expression is derived to compute players' payoff for probability-based belief systems in the proposed game modelling. The algorithms and game modelling have no frequency constraint; thus, they will work in all frequency bands of the radio spectrum, and any radio communication system with dynamic spectrum sensing and transmission capability available at present or in the future can use the proposed anti-jamming technique. The latest research considers the software defined radio for developing the transmitter and receiver component of the 5G network technology[14] due to the ease of baseband signal processing. The use of SDR enables the dynamic spectrum sensing and transmission capability in the 5G networks, so the Open Radio Access Network[15] (ORAN) standardisation may consider the proposed Perfect Hidden Markov- Viterbi equilibrium solution concept to overcome the challenges posed by the jamming attack on the 5G networks in the ORAN security specifications.

The organisation of this paper is as follows. Section 2 discusses the communication model of cognitive radio nodes with PBE and proposed Perfect Hidden Markov- Viterbi equilibrium solution concepts under multiple jammer attacks. Then, in Section 3, we derive a general form of the expression for the game theory-based perfect hidden Markov - Viterbi equilibrium solution concept. Simulation results are discussed in Section 4. Conclusions are given in Section 5.

2. COMMUNICATION MODEL

In the proposed system, apart from the standard components, such as Additive White Gaussian Noise (AWGN) and fading channel coefficient, the communication channel has noise (j_1 to j_m) introduced by multiple jammers. The following Eqn. can express the wireless model:

$$y=h(x) + n + \sum_{i=1}^{m} j_i \tag{1}$$

where, y is the received signal, x is the transmitted signal, h is the fading channel coefficient, n is the additive white Gaussian noise with mean = 0 variance, $=\sigma^2$,j is the jamming signal, and i=1 to m.

2.1 Channel Selection-Perfect Bayesian Equilibrium

The Perfect Bayesian equilibrium[16] solution concept is used to model the CR interactions with the jammer and compute its payoff. Decision-making is based on Bayes' rule to classify the jammer as strong or weak. If the jammer can identify CR transmission and interrupt more than 30 %, which can considerably degrade analog voice communication 17, it is classified as a strong jammer; otherwise, it is classified as a weak jammer.

$$P(E_i | A) = \frac{P(E_i)P(A \mid E_i)}{\sum_{i=1}^{k} P(E_i)P(A \mid E_i)} \tag{2}$$

where, in Bayes' rule[18], $P(E \mid A)$ is the posterior probability, $P(A \mid E)$ is the likelihood, P(E) is the prior probability, P(A) is the evidence and i=1 to k. Eqn. (2) helps to quantify beliefs as a probabilistic value from 0 to 1.

The algorithm to classify the jammer type and decide on the channel for cognitive radio transmission based on the Perfect Bayesian equilibrium solution concept is given in Fig. 1. The cognitive radio node starts with spectrum sensing in the radio environment to identify channel availability for secondary user transmission since we use the energy detection spectrum sensing technique[19]. Any channel detected with an energy level above the set threshold E_T (i.e., power spectral density of 1 kHz) is considered busy. The channel can be either occupied by the primary user or noisy, which is not favourable for CR transmission. It is always ensured that channels the primary

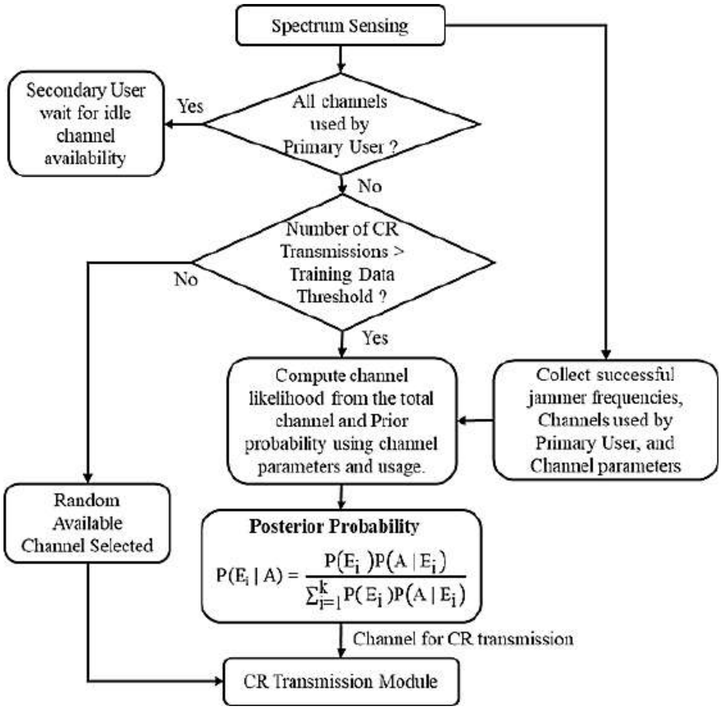


Figure 1. Algorithm to classify the jammer type and channel for transmission using perfect Bayesian equilibrium technique.

user uses are not considered for CR transmission; thus, the CR will wait until an idle channel for transmission. For Bayesian decision-making, the prior probability is essential. To compute the prior probability, we need some training data. Therefore, we initially use random channels for CR transmissions and collect primary user channels, frequencies of jammers successfully blocking CR transmission, and channel parameters to build the training dataset. The training data threshold, a user-defined value, is the number of CR transmissions required to collect the necessary data.

2.2 Channel Selection–Perfect Hidden Markov-ViterbiEquilibrium

The operations of the channel selection algorithm for cognitive radio nodes, from spectrum sensing using the energy detection technique to training data threshold setting, i.e., the three initial steps, are the same as described in Section 2.1. However, the algorithm differs after the user-defined training data threshold limit check module is reached. Here, we use the Hidden Markov Model (HMM) - Viterbi decoding for decision-making in place of Bayes' rule.

Though both HMM and Bayes techniques use probabilistic reasoning, the HMM also considers hidden states based on the emissions. This inherent feature of HMM helps improve decision-making in incomplete information anti-jamming games.So, the proposed technique is aptly renamed Perfect Hidden Markov – Viterbi equilibrium to depict the change in the Perfect Bayesian equilibrium solution concept. The source of data required to compute the initial, transition, and observation probabilities of the Hidden Markov Model are depicted in Fig. 2. It is assumed that once cognitive radio is switched on, it continuously observes the radio environment by sweeping through all in scope frequencies bands to obtain its current status. It builds initial, transitional, and observational probability tables.At the time of analysis, the latest table values are used for channel state estimation. The initial and transition probabilities represent three states: channel busy, not favourable (High noise or deep fade), and channel idle.

The observation probability is computed by observing three emissions[12] from the channel namely, below threshold frequency (E_T), high noise, and high transmission power (high noise or higher transmission frequency demand more power). The algorithm to classify the jammer type and decide on the channel for cognitive radio transmission based on the proposed perfect hidden Markov - Viterbi equilibrium solution concept is provided in Fig. 3.Primarily, channels deduced to be idle or not favourable by the HMM-Viterbi algorithm is considered for CR transmission. If there are no idle or unfavourable channels, even a channel deduced to be busy is considered for transmission. The busy channel here does not include channels currently used by the primary user; those channels are already filtered in the second stage of the algorithm. However, in all cases, the proposed algorithm based on available data ensures that a deduced channel least used by the primary user and least affected by channel impairments, including jamming interference, is selected for CR transmission.

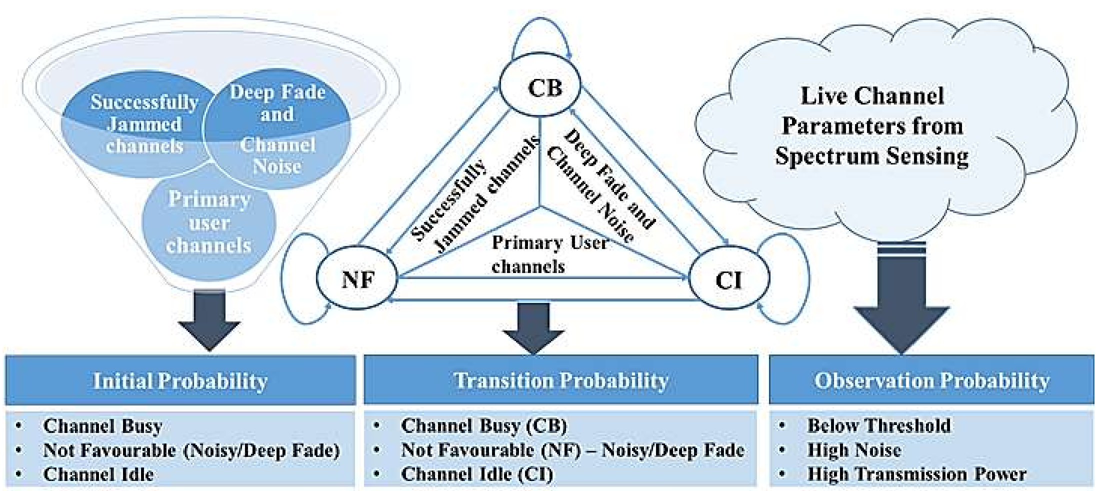


Figure 2. Source of initial, transition, and observation probabilities of HMM.

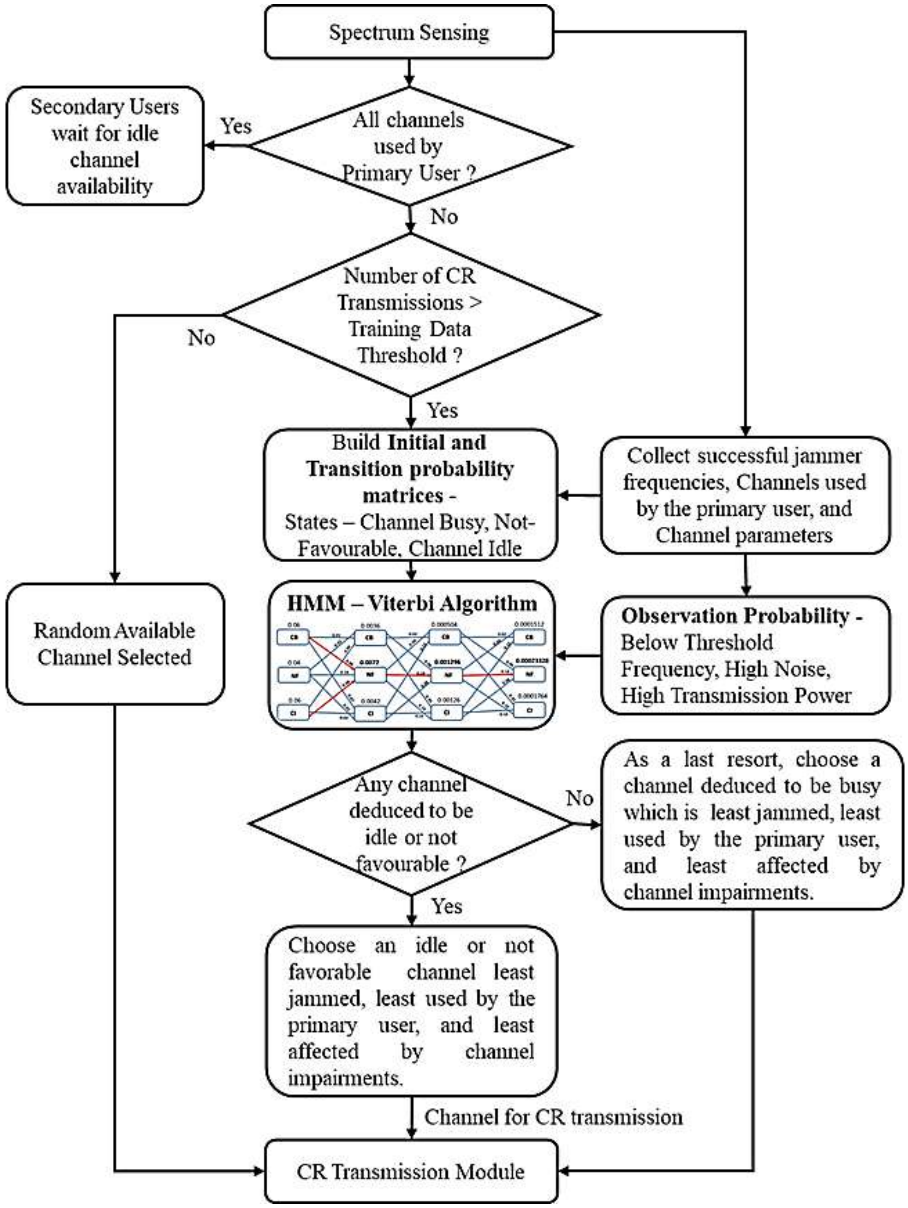


Figure 3. Algorithm to classify the jammer type and channel for transmission using perfect hidden markov-viterbi equilibrium technique.

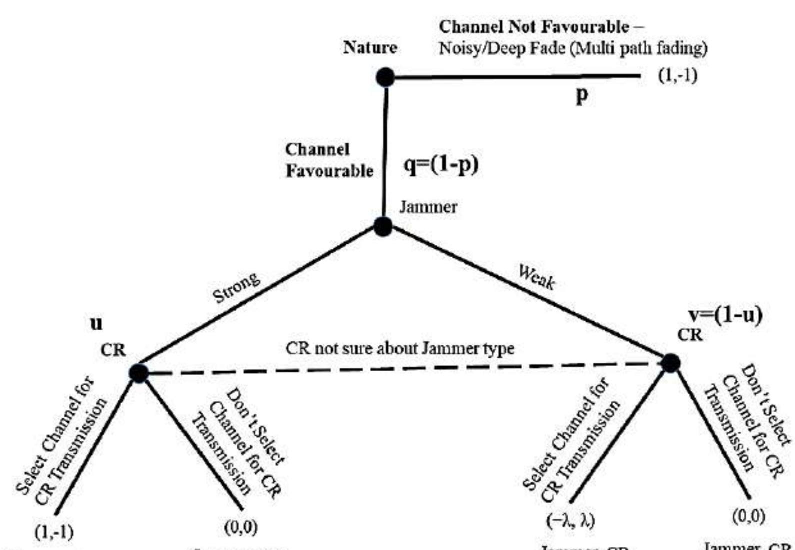


Figure 4. Game tree of the incomplete information strategic form game.

3. PERFECT HIDDEN MARKOV-VITERBI EQUILIBRIUM

The game model has three players: Nature (representing channel impairment), jammer, and cognitive radio with sequential moves. Typically, sequential games with incomplete information use the Perfect Bayesian equilibrium solution concept, where beliefs are determined by Bayes' rule to identify the player type.

In the proposed solution, beliefs are determined by the Hidden Markov Model - Viterbi decoding instead of Bayes' rule to identify the jammer type. Based on the jammer's ability to successfully jam a channel used by a cognitive radio node, its type is classified as either strong or weak. Figure 4 depicts the game tree, where, λ=1-τ, i.e., the cost of the jammer for missing CR transmission. Here, the jammer's cost is CR's payoff, λ[0,1]. The cost of CR for transmission loss due to jamming is $\tau\in[0,1]$. The probability that nature decides on a channel to be impaired with high noise or a deep fade event is $p\in[0,1]$ which indicates an unfavourable channel in this context. The likelihood of the channel being free of high noise or deep fade events is a favourable channel, q=(1-p) and $q\in[0,1]$. The probability of the jammer being strong is $u\in[0,1]$ and weak is v=(1-u) and $v\in[0,1]$. The values p,q,u and v are beliefs of the CR node.Every channel available to the CR node in the radio environment is individually assessed using the game tree and the channel selection for CR transmission is based on payoffs. The proposed algorithm based on the Perfect Hidden Markov- Viterbi equilibrium solution concept will always strive to maximize its payoff compared to the jammer by choosing the optimal strategy to avoid poor channels and evade jammers to reduce the BER.

3.1 Strategic Form Game with Incomplete Information

A strategic form game with incomplete information is defined as a tuple.

$$\Psi=\langle N, (\Omega_i), (S_i), (p_i), (u_i), (\rho_i)\rangle$$

where,

1) N={1,2,…,n} is the set of players.
2) Ω_i is the set of types of player i where i=1,2,…,n.
3) S_i is the set of pure strategies of player i, where, i=1,2,…,n..
4) The belief function p_i is a mapping from Ω_i into $\Delta(\Omega_{-i})$, probability distributions over Ω_{-i}. Any possible type $\omega_i\in\Omega_i$, p_i specifies a probability distribution $p_i(.|\omega_i)$ over the set Ω_{-i} representing player i's beliefs about the types of other players if its type was ω_i.
5) The belief function u_i is a mapping from η_i into $\Delta(\eta_{-i})$, probability distributions over η_{-i}. Any possible type $\varepsilon_i\in\eta_i$, u_i specifies a probability distribution $u_i(.|\varepsilon_i)$ over the set η_{-i} representing player i's beliefs about the types of other players if its type was ε_i.

The payoff function ρ_i: $\Omega_1\times..\times\Omega_n\times S_1\times..\times S_n\rightarrow\mathbb{R}$ assigns each profile of types and actions a payoff that player i will receive.

3.1.1 Strategies and Expected Utility

Some information of incomplete information games are known to one player and unknown to other players. Nature has no strategic objectives as a player, as it does not expect any payoff for its action. Player strategies in the game can be defined as follows:

$$S_0^{\text{Nature}} = \{\text{Favourable, Not Favourable}\}$$

$$S_1^{\text{Strong Jammer}} = \{\text{Transmit, Do not Transmit}\}$$

$$S_1^{\text{Weak Jammer}} = \{\text{Transmit, Do not Transmit}\}$$

$$S_2^{\text{Cognitive Radio}} = \{\text{Transmit, Do not Transmit}\}$$

where,

$$S \in S_0^{\text{Nature}}\times S_1^{\text{Strong Jammer}}\times S_1^{\text{Weak Jammer}}\times S_2^{\text{Cognitive Radio}}$$

The strategy profile and beliefs of the three players are given below.

$$\left\{\begin{array}{c}\text{(Favourable, Not Favourable), (Transmit,}\\ \text{Do not Transmit),}\\ \text{(Transmit, Do not Transmit), p, q, u, v}\end{array}\right\}$$

In the presence of a strong jammer, the expected utility of the cognitive radio node for strategies {Favorable, Trasmit, Transmit, p, q, u, v} and {Favorable, Trasmit, Do not Transmit, p, q, u, v} are as follows:

$$EU_2(\text{Transmit})=(-1(qu) + \lambda(qv)) \quad (3)$$
$$EU_2(\text{Do not Transmit})=(0(qu) + 0(qv)) \quad (4)$$
$$EU_2(\text{Do not Transmit})=0 \quad (5)$$

Eqn. (3), can be algebraically reduced to find a general form of expression to compute the expected utility of CR, where λ=(1-τ), q=(1-p), and v=(1-u).

$$EU_2(\text{Transmit})=(-1((1\text{-}p)u) + \lambda(qv)) \quad (6)$$
$$EU_2(\text{Transmit})= (-1((1\text{-}p)u) + (1\text{-}\tau)(1\text{-}p)(1\text{-}u)) \quad (7)$$
$$EU_2(\text{Transmit})= (-u + pu + 1 - u - p + pu - \tau + \tau u + \tau p - \tau pu) \quad (8)$$
$$EU_2(\text{Transmit})= (1 - 2u + 2pu - p -\tau + \tau u + \tau p - \tau pu) \quad (9)$$
$$EU_2(\text{Transmit})= (1 - 2u + 2pu - p + \tau(-1 + u + p - pu) \quad (10)$$
$$EU_2(\text{Transmit})= (1 + 2u(p - 1)- p + \tau((u - 1)+ p(1 - u)) \quad (11)$$
$$EU_2(\text{Transmit})=q + 2u(-q) + \tau(-v + pv) \quad (12)$$
$$EU_2(\text{Transmit})=q(1 - 2u) + \tau(-v + pv) \quad (13)$$
$$EU_2(\text{Transmit})=q(1 - 2u) + \tau v(p - 1) \quad (14)$$
$$EU_2(\text{Transmit})=q(1 - 2u) + \tau v(-q) \quad (15)$$
$$EU_2(\text{Transmit})=q(1 - 2u)- \tau vq \quad (16)$$
$$EU_2(\text{Transmit})=q((1 - 2u)- \tau v) \quad (17)$$
$$EU_2(\text{Transmit})=q[1 - (2u + \tau v)] \quad (18)$$

The general form of the expression derived in Eqn (18), can be used to compute players' payoff for probability-based belief systems in the proposed type of game modelling. It can be seen via q that the natural channel impairments substantially influence the system. The best response of the player in the Prefect Hidden Markov - Viterbi equilibrium solution concept can be achieved primarily based on the player's ability to find the jammer's strength concerning a channel and classify it as strong or weak by determining the values of beliefs u and v. When the player is very confident that the jammer is good at jamming a particular channel, u=1; otherwise, if the jammer is not detecting and jamming transmission u=0, which makes v=1, as v=(1-u), the expected utility of the CR node for the strategy profile with favourable channel q=1 and the weak jammer are given as follows.

$$\text{Strategy}\longrightarrow\left\{\begin{matrix}\text{Favourable, weak, Transmit,}\\ p=0,\ q=1,\ u=0,\ v=1\end{matrix}\right\} \tag{19}$$

$$EU_2(\text{Transmit})=\lambda(qv)+\left(-1(qu)\right) \tag{20}$$

$$EU_2(\text{Transmit})=\lambda(1)+\left(-1(0)\right) \tag{21}$$

$$EU_2(\text{Transmit})=\lambda \tag{22}$$

When we substitute values of beliefs in Eqn. (18), we obtain the same result as in Eqn. (22).

$$EU_2(\text{Transmit})=1[1-(2(0)+\tau(1))] \tag{23}$$

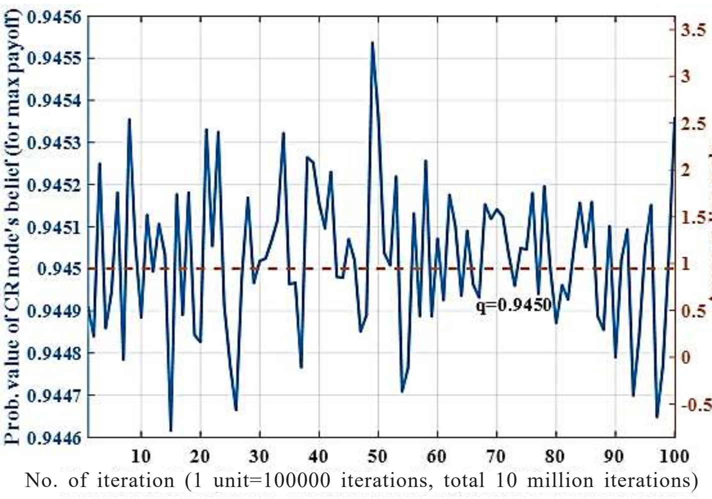
$$EU_2(\text{Transmit})=[1-\tau] \tag{24}$$

$$EU_2(\text{Transmit})=\lambda \tag{25}$$

$$\text{Strategy}\longrightarrow\left\{\begin{matrix}\text{Favourable, weak, Do not Transmit,}\\ p=0,\ q=1,\ u=0,\ v=1\end{matrix}\right\} \tag{26}$$

$$EU_2(\text{Do not Transmit})=0(qv)+0(qu) \tag{27}$$

$$EU_2(\text{Do not Transmit})=0 \tag{28}$$



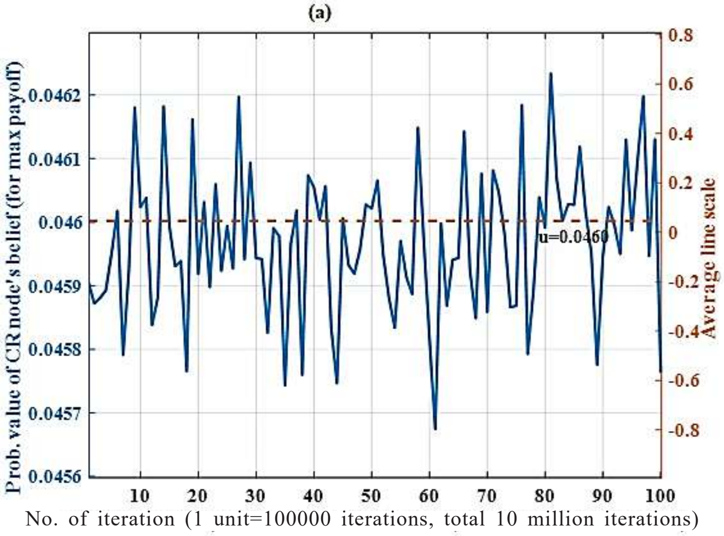


Figure 5. Probability distribution of beliefs, (a) Probability distribution of cognitive radio's belief at a decision node on a favourable channel for a maximum payoff; and (b) Probability distribution of cognitive radio's belief at a decision node on a jammer type for a maximum payoff.

While comparing player 2, the CR node's strategies Transmit and Do not Transmit based on the expected utility given at Eqn. (22) and Eqn. (28), it was found that the strategy and beliefs shown in Eqn. (19) gain a higher payoff than the strategy profile at Eqn. (26), i.e., $\lambda>0$. λ is the cost of the jammer for missing CR transmission, and $\lambda\in[0,1]$.

The numerical analysis performed using Eqn. (18), shows that the probability value of q, which represents the favourable channel for achieving maximum payoff in the presence of a weak jammer, averages 0.9450 for ten million iterations.When the jammer type is weak, any value of $q>0.9450$ provides a higher payoff to the cognitive radio node than the jammer. Similarly, the numerical analysis is performed using Eqn. (18), to find the optimal u value, representing the strong jammer type to achieve the maximum payoff for CR against the jammer averaging 0.0460 for ten million iterations.The probability distribution of CR's belief concerning channel type and jammer type for maximum payoff is displayed in Fig. 5.Hence, when the channel is favourable, without deep fade or channel noise events, any value of $u<0.0460$ will provide a higher payoff. From the simulation, we understand that when a weak jammer transmits to block CR transmission under favourable channel conditions, the strategy and beliefs {Favourable, weak, Transmit, $q>0.9450$, $u<0.0460$} are the Perfect Hidden Markov - Viterbi equilibrium.

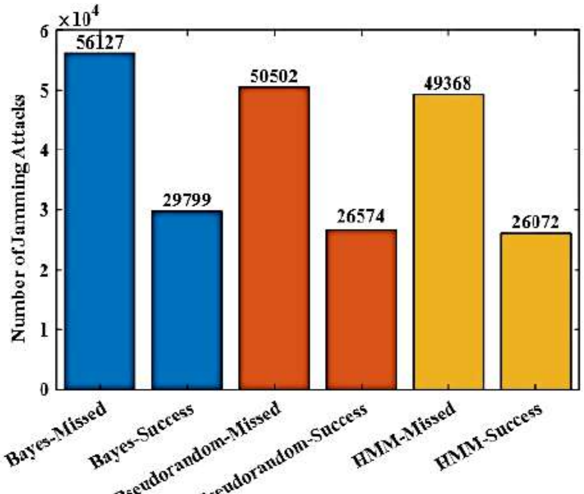
4. RESULTS AND DISCUSSION

The MATLAB simulation results show the performance metrics of an anti-jamming system that uses the Perfect Bayesian equilibrium (PBE) solution concept, the Perfect Hidden Markov - Viterbi equilibrium solution concept, and the pseudorandom-based frequency hopping technique in channel selection for frequency hopping during cognitive radio transmission.

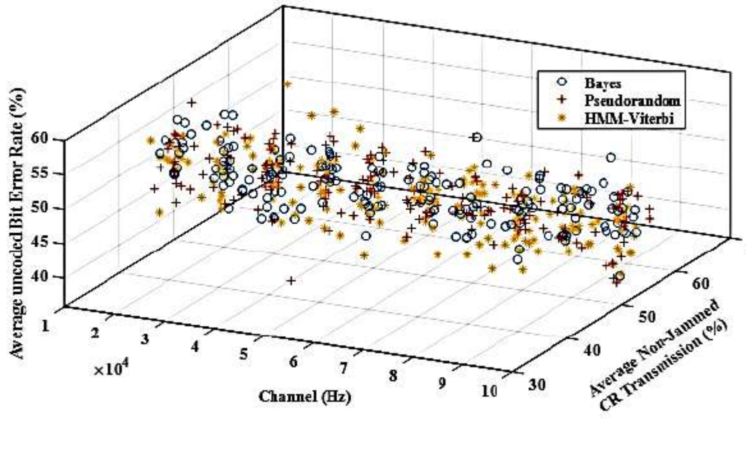
Table 1. Simulation parameters

Parameters	Values
Modulation	Binary phase shift keying[21]
Channel type	Rayleigh fading[22]
Doppler shift	Random relative radial velocity between 0 to 15 m/s
Noise type	Additive white gaussian noise (awgn)
Jammer type	Smart-hybrid jammer
Number of jammers	Random (between 1 to 20) per cr transmission
Maximum jammer power	Random (1 to 10 times cr transmission power)

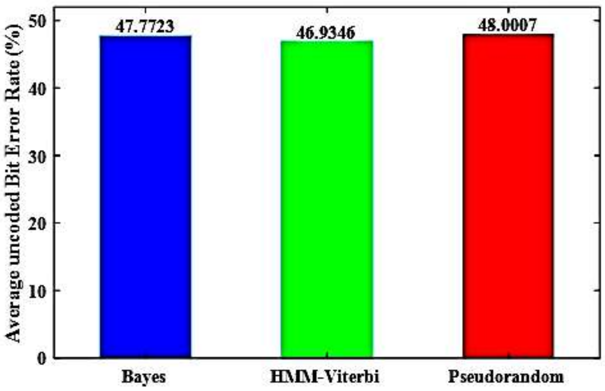
In the simulation, the CR transmissions are sequential, starting with PBE, then the proposed Perfect Hidden Markov - Viterbi equilibrium solution concept, and finally, with the pseudorandom-based frequency hopping technique. A channel is considered high noise when the signal-to-noise ratio (SNR) is less than 4 dB because an SNR below this value results in higher bit error for BPSK in AWGN with interference[20]. The BER is the ratio of the number of bits received in the error over the total number of bits transferred.We individually simulated 5613 cognitive radio transmissions for the Perfect Bayesian


×10^4
Number of Jamming Attacks
56127
29799
50502
26574
49368
26072
Bayes-Missed
Bayes-Success
Pseudorandom-Missed
Pseudorandom-Success
HMM-Missed
HMM-Success

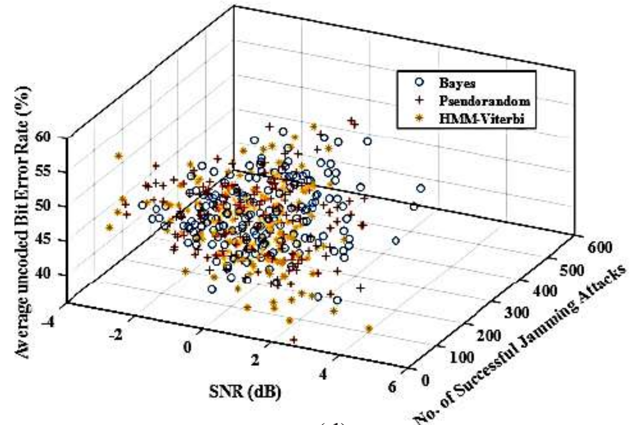
(a)


Bayes
Pseudorandom
HMM-Viterbi
Average uncoded Bit Error Rate (%)
Channel (Hz)
×10^4
Average Non-Jammed CR Transmission (%)

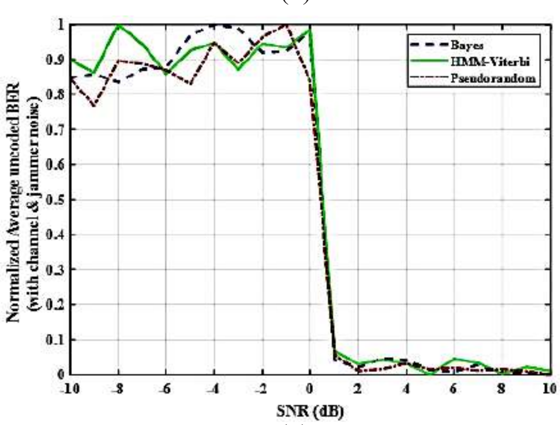
(b)


Average uncoded Bit Error Rate (%)
47.7723
46.9346
48.0007
Bayes
HMM-Viterbi
Pseudorandom

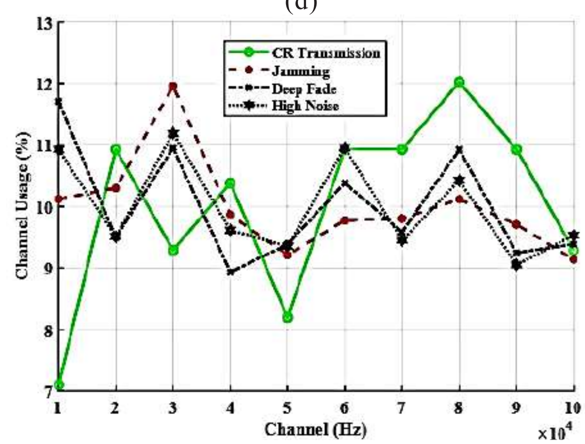
(c)


Bayes
Pseudorandom
HMM-Viterbi
Average uncoded Bit Error Rate (%)
SNR (dB)
No. of Successful Jamming Attacks

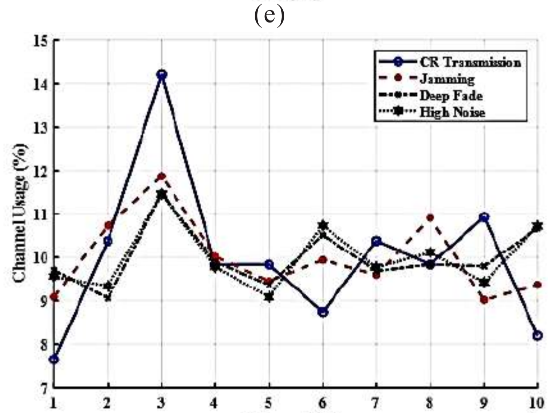
(d)


Bayes
HMM-Viterbi
Pseudorandom
Normalized Average uncoded BER (with channel & jammer noise)
SNR (dB)

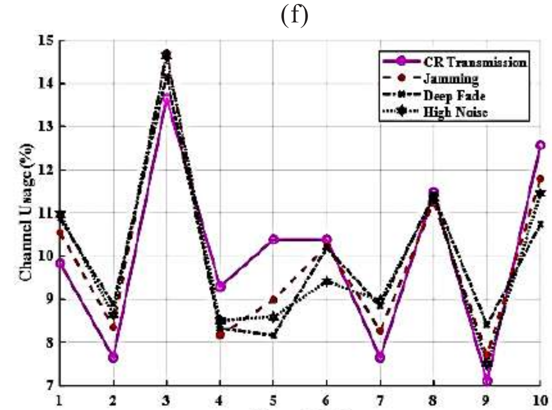
(e)


CR Transmission
Jamming
Deep Fade
High Noise
Channel Usage (%)
Channel (Hz)
×10^4

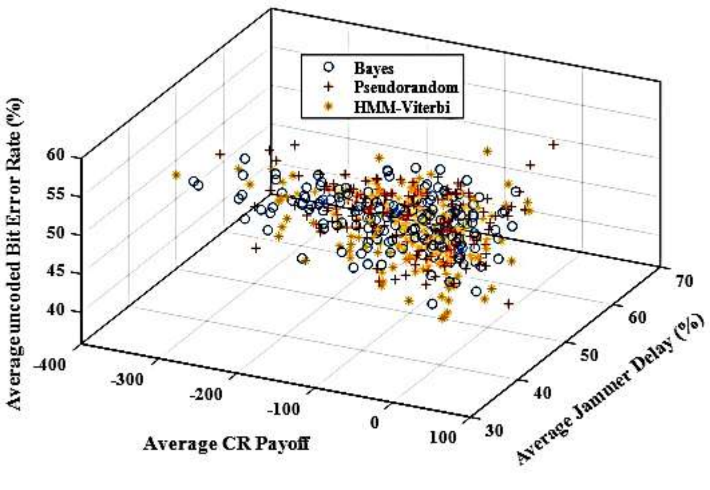
(f)


CR Transmission
Jamming
Deep Fade
High Noise
Channel Usage (%)
Channel (Hz)
×10^4

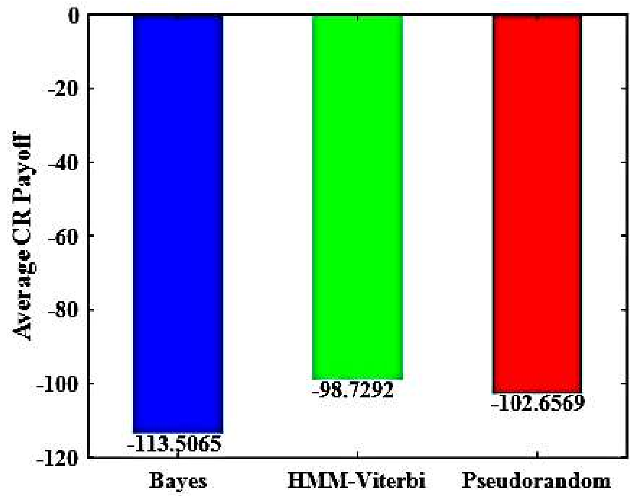
(g)


CR Transmission
Jamming
Deep Fade
High Noise
Channel Usage (%)
Channel (Hz)
×10^4

(h)



(i)



(j)

Figure 6. Performance comparison of Perfect Bayesian equilibrium, Perfect Hidden Markov - Viterbie quilibrium, and pseudorandom frequency hopping techniques, (a) Number of jamming attacks missed and successful; (b) Average uncoded BER in percentage corresponding to the channel used by CR for transmission and average non-jammed CR transmission; (c) Average uncoded BER; (d) Average uncoded BER with SNR and Successful Jamming Attacks; (e) Normalized average uncoded BER; (f) Perfect Hidden Markov - Viterbi equilibrium technique CR channel usage, jamming, and deep fade events; (g) Perfect Bayesian equilibrium technique CR channel usage, jamming, deep fade, high noise events; (h) Pseudorandom technique CR channel usage, jamming, and deep fade events; (i) Average uncoded BER with an average CR Payoff and an average jammer delay; and (j) Average CR Payoff comparison of Perfect Bayesian equilibrium, Perfect Hidden Markov - Viterbi equilibrium, and pseudorandom frequency hopping techniques.

equilibrium, Perfect Hidden Markov - Viterbi equilibrium, and pseudorandom frequency hopping techniques. Fig. 6(a) shows that while using the Perfect Bayesian equilibrium technique, the 5613 cognitive radio transmissions faced 85926 jamming attacks from multiple jammers, of which only 34.68 % succeeded,while 65.32 % of attacks missed CR transmissions. For the Perfect Hidden Markov - Viterbi equilibrium technique, 5613 cognitive radio transmissions faced 75440 jamming attacks from multiple jammers, of which only 34.56 % succeeded and 65.44 % attacked missed CR transmissions. In addition, for the pseudorandom frequency hopping technique, 5613 cognitive radio transmissions faced 77076 jamming attacks from multiple jammers, of which only 34.48 % succeeded and 65.52 % of attacks missed CR transmissions.

From Fig. 6(b), we infer that even in the low channel availability conditions, CR nodes can evade almost 50 % of multiple jammer attacks in all three techniques: the Perfect Bayesian equilibrium, Perfect Hidden Markov - Viterbi equilibrium, and pseudorandom frequency hopping. Fig. 6(c) shows that the CR node using the Perfect Hidden Markov - Viterbi solution concept achieved a lower average bit error rate than the other two techniques.The SNR values in Fig. 6(d) depict the noise caused due to the AWGN only. In addition to the AWGN,the jammer-introduced noise and multipath fading also affect the communication system. In some cases, even if the SNR is high, due to the effect of jammer-introduced noise and multipath fading, an increase in the BER is observed at the receiver. For better understanding, in Fig. 6(e), BER is normalised to plot against SNR; the x-axis of the graph represents the SNR with respect to AWGN only, and the y-axis depicts the bit error caused by the AWGN and multipath fading effect collectively called channel noise,apart from the jammer-introduced noise.It is found that until the AWGN value is depicted as SNR = 0 dB, the bit error rate is high for all three techniques. At SNR = 1 dB, there is a sharp decline in the BER trend after that due to the AWGN reduction in all three techniques under investigation.

It is seen that three techniques, Perfect Bayesian equilibrium, Perfect Hidden Markov - Viterbi equilibrium, and pseudorandom frequency hopping techniques, all perform at the same level in many instances. To determine the reasons for the reduction in average BER while using Perfect Hidden Markov - Viterbi equilibrium, the behaviour of these techniques should be analysed at a more granular level. Therefore, we analyse the events occurring in each available channel. Four events considered for analyses are as follows: usage of the channel by cognitive radio node, jammer introducing interference in a channel, occurrence of deep fade, and channel noise other than jammer interference. The occurrence of an event in a channel can be identified from the channel usage and channel parameter statistics of the Perfect Bayesian equilibrium, Perfect Hidden Markov - Viterbi equilibrium, and pseudorandom frequency hopping techniques. The plot given in Fig. 6(f) for Perfect Hidden Markov - Viterbi equilibrium shows that CR was able to evade the jammer and avoid impaired channels much better than the other two techniques, illustrated in Fig. 6(g) and Fig. 6(h). Therefore, the beliefs updated in the proposed Perfect Hidden Markov - Viterbi equilibrium solution concept to identify the jammer type and channel suitability for CR transmission are more accurate than the beliefs updated via traditional Perfect Bayesian equilibrium or CR transmission using the pseudorandom hopping technique that is utilized to evade the jammer.Regarding payoff, we observe in Fig. 6(i), that a cognitive radio node gains more payoff when the jammer delay is high. This is because when the jammer takes more time to identify and jam a CR transmission in a channel, it indirectly implies that the jammer type is weak. If the channel conditions are favourable, the CR node using strategy Eqn. (19) can gain a higher payoff than the jammer.

The natural channel impairments are a substantial bottleneck in achieving higher and positive payoff. According to Eqn (18), the deep fade and other channel noises considerably influence the system. Since our investigation is on multiple jammer attacks on cognitive radio networks over a noisy channel, the channel conditions are primarily poor. The average CR payoff is negative for all three techniques, as depicted in Fig. 6(i)and Fig. 6(j). Multiple jammer attacks on cognitive radio networks show that jammers mostly cooperate in an incomplete information game theoretical scenario. Otherwise, if the jammers act independently, they end up jamming their peers' transmissions and wasting energy. When players cooperate, there are always delays in decision-making to formulate a strategy on who and when to act, and any miss or delay on the jammers' part can be exploited in the proposed Perfect Hidden Markov - Viterbi equilibrium solution concept to evade the jamming attack.

5. CONCLUSION

Our approach introduces a novel concept, the Perfect Hidden Markov-Viterbi equilibrium, which integrates the Hidden Markov Model and Viterbi decoding algorithm with the game theory. This solution concept is designed to find equilibrium in anti-jamming games with incomplete information under multiple jammer attacks. Based on available data from the simulation, the proposed Perfect Hidden Markov - Viterbi equilibrium solution concept ensures that a deduced channel is least used by the CR primary user and least affected by the channel impairments, including jamming interference,is selected for CR transmission. As a result, over time, with a gradual reduction in bit error rate at the receiver without any channel coding for BPSK modulation and in the noisy Rayleigh fading environment, the Perfect Hidden Markov - Viterbi equilibrium solution under multiple jammer attacks performs better than the Perfect Bayesian equilibrium by 0.8 % and the traditional pseudorandom based frequency hopping technique by 1 % in terms of the average uncoded BER.

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CONTRIBUTORS

Mr. Deepak B R is pursuing PhD under the faculty of Information and Communication Engineering at Anna University, Madras Institute of Technology Campus Chennai, Tamil Nadu, India. His research interests include: Machine learning and game theory applications in wireless communication security.
Contributions to this research work include: The conception of ideas, mathematical formulation, simulation, interpretation of results, and manuscript preparation.

Prof. Dhananjay Kumar obtained his PhD in Information and Communication Engineering from Anna University, Chennai, India. He is a Professor in the Department of Information Technology at Anna University, Madras Institute of Technology Campus, Chennai, India. His research interests are: Wireless communications, machine learning, and media streaming systems.
Contributions to this research work include: Guidance in problem formulation, simulation, analysis of results and manuscript preparation.