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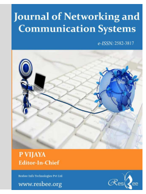

Taylor-based Artificial Lemming Algorithm for Optimized Spectrum Sensing in Cognitive Radio Networks

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Abstract: Cognitive Radio Networks (CRN) are considered an excellent wireless communication system, which allows secondary users to use licensed spectrum without the interference of primary users. In CRN, spectrum sensing is utilized for the identification of the idle frequency bands of the primary user for the utilization of available spectrum. Nowadays, various approaches are used for spectrum sensing by concurrently analyzing multiple frequencies for detecting the activities of the primary user. However, these conventional methods often struggle with scalability, noise robustness, and adaptation to dynamic spectrum environments. Meanwhile, these methods cannot ensure the desired performance results in the utilization of low spectrum resources. Thus, a deep learning with hybrid optimization model, Taylor-based Artificial Lemming Algorithm-Deep Neural Network (TALA_DNN), is designed for spectrum sensing in CRN. The system model of CRN is initially considered, and the cyclic spectrum is used to extract the hidden periodicities in the received signal. The use of cyclostationary analysis enhances the robustness of the model by capturing signal features that remain stable over time, even in the presence of noise. Then, the spectrum sensing is detected by Deep Neural Network (DNN), where the sensing performance of DNN is increased by training utilizing Taylor-based Artificial Lemming Algorithm (TALA). TALA combines the bio-inspired exploration stategies of the Artificial Learning Algorithm with the convergence refinement of Taylor seris expansion, optimizing DNN hyperparameters efficiently. Further, the performance of TALA_DNN in performing spectrum sensing is investigated. The TALA_DNN showcases superior performance with a probability of false alarm of 5.83x10-5, a probability of detection of 0.9999, and a computational time of 0.199 sec. These results indicate the potential of TALA-DNN as a viable model for real-time, high-accuracy spectrum sensing in next-generation CRN applications.

Keywords: Taylor Series, Artificial Lemming Algorithm, Deep Neural Network, Cognitive Radio Networks, Spectrum Sensing

Nomenclature

Abbreviation	Description
CRN	Cognitive Radio Network
PU	Primary User
SU	Secondary User
DNN	Deep Neural Network
TALA	Taylor-based Artificial Lemming Algorithm
ALA	Artificial Lemming Algorithm
FFT	Fast Fourier Transform
FAM	FFT Accumulation Method
SNR	Signal-to-Noise Ratio
SCF	Spectral Correlation Function
CAF	Cyclic Autocorrection Function
AWGN	Additive White Gaussian Noise
QoS	Quality of Service
MSE	Mean Square Error
CNN	Convolutional Neural Network
STFT-RADN	Short-Time Fourier Transform-Residual Attention Dense Network
Fractional GWO-CS	Fractional Grey Wolf Optimization combined with Cuckoo Search
DBN	Deep Belief Network
3EED	Three Event Energy Detection

1. Introduction

With an increasing demand for bandwidth technologies due to data-intensive applications and a surge in connected devices, the landscape of wireless communication is evolving rapidly [8]. Nowadays, the radio spectrum has a significant impact on our day-to-day lives in providing various real-time applications [2]. Due to the continuous growth of wireless devices and the manner the devices are organized, the radio spectrum is not available easily. Radio spectrum scarcity is considered one of the common issues encountered by future communication research that needs to be solved [4]. Meanwhile, the static management of the radio spectrum and rapid utilization of wireless devices leads to a shortage the available spectrum [1]. This scarcity not only limits user access but also negatively impacts network quality, latency, and the deployment of emerging technologies such as IoT, 5G, and autonomous systems. Cognitive Radio (CR) technologies are used to handle the issues in the radio spectrum [4], where CRN acts as an effective solution for spectrum resource scarcity issues. In 1999, Mitola introduced the concept of CRN as an intelligent wireless communication system, which allows SUs to use licensed spectrum without the interference of PUs [1]. Generally, the allocated spectrum is only used by the licensed PU in traditional static spectrum allocation systems, and the radio resources of PUs cannot be accessed by unlicensed SUs, even when not in use. Thus, it is vital to use underutilized spectrum bands in order to prevent the denial of essential radio demands [3]. Spectrum sensing is used in CRN to enable SUs to identify the occupied frequency bands of the PUs for the utilization of available spectrum more substantially [1]. This dynamic access mechanism allows for real-time spectrum reuse, enhancing overall spectrum efficiency while minimizing interference.

In CRN, spectrum sensing is considered a pivotal operation [8], which is used to monitor and detect spectrum holes [7]. Nowadays, spectrum sensing has attained significant attention among researchers because of the increasing utilization of CRN [8]. The major role of spectrum sensing is the utilization of spectrum bands by SUs without disturbing the communication of PUs by effectively detecting the spectrum holes while maintaining the required QoS and throughput [12]. The classical spectrum sensing methods are categorized into three distinct types, such as cyclostationary, matched filtering detection, and energy detection, where sensing algorithms are used based on the signal transmitted by the users [7][11]. These methods utilize decision theory and statistical models for making informed decisions on the time off and existence of the signals based on prior knowledge and observed data [8]. However, these traditional methods often suffer from limited accuracy in low SNR conditions and are less effective in dynamic or heterogeneous spectrum environments. At present, various research works on machine learning techniques have been performed and studied for spectrum sensing in CRN [9][10]. Typical machine learning approaches, namely Naive Bayes classifier as well as support vector machines, are utilized to increase the sensing performance by overcoming the drawbacks of traditional spectrum sensing methods. However, the baseline machine learning methods mainly depend on domain knowledge and require a time-consuming manual feature extraction process [3]. At present, deep learning techniques are utilized to classify huge databases by viewing spectral sensing as a binary classification issue to identify the absence or presence of the signal of the PU in complex wireless data. Deep-learning-based spectrum sensing is more robust and has attained high accuracy in high-interference and complex wireless environments. Deep learning techniques, like CNN, DNN, and so on, outperform other machine learning algorithms [1]. These models automatically learn hierarchical features from raw input data, eliminating the need for handcrafted feature engineering.

This paper introduces TALA_DNN for spectrum sensing in CRN, where the system model of CRN is initially taken into account. Then, the signal received from the CRN is applied to the cyclic spectrum to extract hidden periodicities. This step leverages cyclostationary signal analysis to identify unique spectral features even in noisy environments. Following this, the spectrum sensing is executed by DNN, where the performance of DNN is increased by fine-tuning using TALA to increase the detection performance. TALA serves as an optimization strategy that dynamically adjusts the hyperparameters of the DNN, enhancing its convergence, accuracy, and generalization capability.

The key contribution is given as,

- ***Designed TALA_DNN for spectrum sensing:*** The DNN is used for spectrum sensing by training the hyperparameters using TALA, where TALA is the incorporation of Taylor series with the ALA. This hybridization allows the model to exploit the global search ability of ALA and the local approximation strength of the Taylor series for improved optimization.

The remaining sections are organized as follows: the review of related work is elucidated in section 2. In section 3, the system model of CRN is depicted, and section 4 portrays the TALA_DNN designed for CRN spectrum sensing. Furthermore, section 5 details the outcomes of the experiment and the discussions performed. Also, in section 6, the article is concluded with a potential future scope.

2. Motivation

With the increasing utilization of intelligent wireless systems, reliable and fast spectrum sensing methods are adopted in CRN to accurately observe the activities of PUs. Various approaches were used in recent years for detecting the activities of PUs without any prior knowledge. However, the previous works did not ensure the desired performance, resulting in the utilization of low spectrum resources. Most conventional and even some machine learning-based models lack adaptability to varying channel conditions, noise uncertainty, and user dynamics. Hence, it encourages to introduce optimization-enabled deep learning approach for spectrum sensing. Such an approach has the potential to combine the automatic feature learning capability of deep learning with the convergence efficiency of metaheuristic optimization, thereby improving sensing accuracy, robustness, and scalability in dynamic CRN environments.

2.1. Literature Review

Wang, A., *et al*. [1] designed STFT-RADN for spectrum sensing in CRN. The STFT-RADN was more robust and attained high detection probability with high efficacy under low conditions of SNR. This method effectively extracted temporal and spectral features from the signal using STFT, while the residual attention mechanism improved focus on informative regions. Meanwhile, this approach failed to perform multiuser cooperative spectrum sensing methods to explore the application of RADN. Kannan, K., *et al*. [2] developed Fractional GWO-CS for spectrum sensing in CRN. The hybridization of GWO and Cuckoo Search enhanced the balance between global and local search in the optimization process. This approach had better convergence and recorded the minimum computational time during spectrum sensing in CRN. Meanwhile, this approach failed to perform spectrum sensing in real-time scenarios. Abdelbaset, S.E., *et al*. [3] established a CNN model for the identification of unused frequency bands in CRN. The CNN model attained high generalizability during spectrum sensing, but this approach failed to perform comparisons by transitioning the model to hardware. Consequently, its practical feasibility for real-world implementation remains unverified. Saraswathi, M. and Logashanmugam, E., [4] introduced DBN-enabled spectrum sensing in CRN. This approach was reliable in addressing communication overhead issues; it leverages unsupervised pretraining and layer-wise learning to capture spectrum characteristics efficiently. However, this approach failed to utilize adaptive learning techniques to adapt and continuously learn various spectrum settings. Mallick, S., *et al*. [5] devised a Detection 3EED model for spectrum sensing. This approach effectively increased the detection rate and maximized the efficiency of spectrum utilization under less computational time. The model achieved this by evaluating three distinct energy thresholds for more precise signal classification. Although this model was not successful in addressing the trade-off issue between energy efficiency as well as spectrum efficiency during the spectrum sensing framework to obtain a realistic CR platform.

2.2. Challenges

The drawbacks of previous schemes used are listed as follows,

- The STFT-RADN approach used in [1] was more robust and attained high detection probability while capturing the signal characteristics for spectrum sensing. However, this model was not successful in using lightweight neural networks for increasing the detection rate in spectrum sensing. The absence of lightweight architectures limits its suitability for resource-constrained devices or edge-based CRN implementations.
- The CNN approach used in [4] effectively minimized the computational overhead issues while distributing spectrum resources, thereby addressing spectrum scarcity issues. Meanwhile, this approach utilized high resource requirements for spectrum sensing. This creates a trade-off between system-level scalability and real-time deployability of the model in dense or energy-limited environments.
- The 3EED spectrum sensing algorithm used in [5] attained high sensing ability and low sensing duration to increase the chance of spectrum sensing using available spectrum holes. However, this model recorded high computational time for sensing using the available hole. Such computational delay can hinder timely decisions, especially in rapidly changing spectrum scenarios where latency is critical.
- The prevailing techniques used for spectrum sensing effectively increased the performance by resolving cognitive reconfiguration and dynamic adaptation capability issues. However, these methods were expensive and did not apply to all modulation signals for spectrum sensing. Their performance often degrades when faced with unfamiliar signal types or when deployed across diverse communication protocols.

3. System Model of CRNs

Let us consider a CRN with an unknown signal structure of the PU, and the power is allocated for transmitting a deterministic pilot tone. The CRN [12][13] spectrum sensing model is used in various communication systems for the synchronization of data frames using a pilot tone. This pilot tone acts as a reference signal, allowing SUs to detect the presence or absence of the PU's transmission more effectively, even under uncertain or dynamic propagation conditions. The spectral sensing issue in CRN is given by,

$$p(t)=\begin{cases}\delta(t) & when\,the\,primary\,user\,is\,absent\\ 2\sqrt{D_u}\,g(t)\cos(2\pi q_0 t+\alpha_0)+\delta(t) & when\,the\,primary\,user\,is\,present\end{cases} \tag{1}$$

In the expression, $g(t)$ is the transmitted signal at time t, the noise is represented by $\delta(t)$, the initial phase and power of the carrier are given by α_0 and D_u, and the carrier frequency is denoted by q_0. Further, linear filtering is executed for the mitigation of any interference from users operating in a non-overlapping band. The whole spectrum is scanned by the SU for the detection of the availability of a spectrum hole.

Consider the signal received by CRN is transferred to the base station, where the equivalent complex baseband is defined for the received signal $p(t)$. Thus, the expression of the received signal $p(t)$ in the availability of a fading environment with thermal noise is expressed by

$$p(t)=u(t)*g(t)+\beta(t) \tag{2}$$

where the complex AWGN is represented as $\beta(t)$, and the impulse response is signified as $u(t)$. The signal detection process is modelled by a binary hypothesis test in the Radio Frequency (RF) spectrum based on the state of the mobile propagation channel, and is expressed as,

$$p(t)=\begin{cases}u(t)*g(t)+\beta(t), & W_1\\ \beta(t), & W_0\end{cases} \tag{3}$$

Here, the hypotheses for the availability of noise are signified as W_1 and W_0. In Fig. 1, the system model of CRN is displayed.

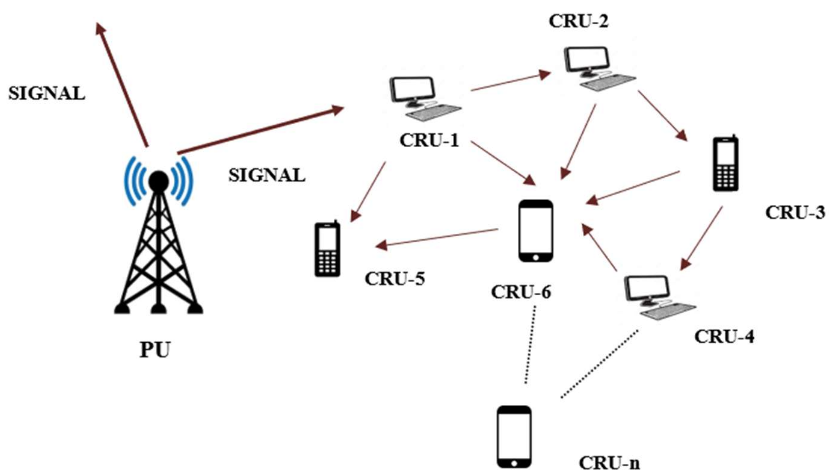


Fig. 1. *System model of CRN*

4. Designed TALA_DNN for Spectrum Sensing

This paper presents the TALA_DNN model designed for spectrum sensing. The system model of CRN is considered initially, and then, the received signal from CRN is subjected to cyclic spectrum, which is used in cyclostationary analysis for the extraction of hidden periodicities. Cyclostationary signal processing leverages the inherent periodic properties of modulated signals, enabling robust detection even in the presence of noise and interference. After that, the spectrum sensing is performed using DNN [14], where the performance is increased by fine-tuning the hyperparameters of DNN using TALA. This hybrid optimization process aims to minimize error and maximize detection accuracy by navigating the solution space effectively, avoiding local minima. The TALA is designed by incorporating the Taylor series [6] with ALA [15]. In Fig. 2, the systematic view of TALA_DNN for spectrum sensing is displayed.

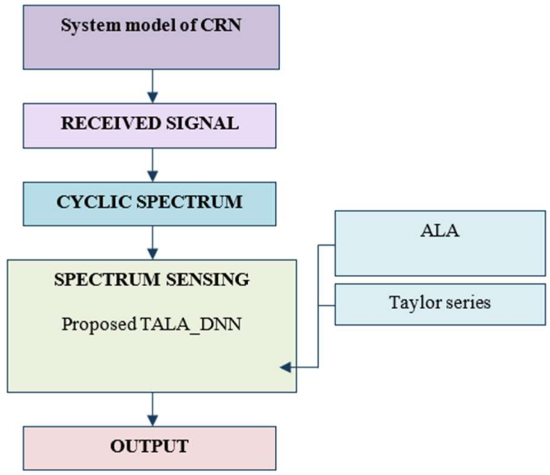


Fig. 2. *Systematic view of TALA_DNN for spectrum sensing in CRN*

4.1. Cyclic Spectrum

This feature plays a key role in identifying the signals even in the presence of noise. At first, the signal $p(t)$ received by the CRN spectrum sensing framework is subjected to cyclostationary signal processing for the extraction of periodicities. Here, the information required for identification is provided by the unique characteristics of different signals exhibited by periodicities. The cyclostationary feature is used to get the statistical characteristics of the received signal $p(t)$ for identifying the unknown transmitted signal $g(t)$ based on multipath fading without any prior knowledge, in the presence of complex AWGN $\beta(t)$. Thus, the second-order cyclostationary of the received signal $p(t)$ is designated by,

$$K_T(t) = \mathrm{E}\left\{p(t+T/2)\,p^*(t-T/2)\right\} \tag{4}$$

In the expression, the autocorrelated received signal $p(t)$ is signified as $K_h(t)$. Let us consider the periodic autocorrelated function with time lag T for second-order cyclostationary signals. Thus, the expression of second-order cyclostationarity $K_h(t)$ based on the Fourier series expansion is expressed by,

$$\mathbb{R}_p^{\delta}(T) = \frac{1}{T_0}\int_{-T_0/2}^{T_0/2} K_T(t) e^{-j2\pi\delta t}\, dt \tag{5}$$

where the cyclic frequency is given by δ, and the Cyclic Autocorrelation Function (CAF) is signified by $\mathbb{R}_p^{\delta}(T)$. Moreover, when the cyclic frequency δ is fixed, then the Fourier transform is given based on the cyclic Wiener relation, and is expressed as,

$$A_p(f) = \int_{T/2}^{T/2} \mathbb{R}_p^{\delta}(T) e^{-j2\pi fT}\, dT \tag{6}$$

Here $A_p(f)$ is the SCF. In general, the SCF recorded high computational complexities, where the SCF is minimized by utilizing the FAM. Thus, the expression of SCF is given by,

$$A_{p_T} = \sum_l J_T(lM, f) J_T^*(lM, f) H_d(b-l) e^{-j2\pi lw/h} \tag{7}$$

In the expression, the complex demodulation of l^{th} windowed segment is represented as $J_T(b, f)$, and is expressed as,

$$J_T(b, f) = \sum_{l=-G'/2}^{G'/2} \mu(l) p(b-l) e^{-j2\pi f(b-l)T_s} \tag{8}$$

Here, h signifies length, the sample size of hopping blocks is symbolized as M, the sampling period is represented as T_s, the channelization length is denoted by G', and the data tampering windows are specified as $\mu(b)$ and $H_d(b)$. Further, the FAM follows bi-frequency mapping, P-point, complex multiplication, $G'-$-point FFT, windowing, and channelization. Also, the input matrix N_l^{SCF} is applied to the classifier model, and is articulated as,

$$N_l^{SCF} = \left|A_{p_T}(b, M, f)\right| \tag{9}$$

After the extraction of hidden periodicities in the received signal, the cyclostationary feature N_l^{SCF} is fed into the DNN model for spectrum sensing, where the process executed is briefly delineated in the upcoming section.

4.2. Spectrum Sensing using ALA_DNN

Spectrum sensing is the process of enabling the SU to identify frequency bands unoccupied by PUs to significantly enhance the available spectrum utilization. Here, the spectrum sensing is performed using DNN [14] from the cyclostationary feature N_l^{SCF} . The sensing performance of DNN is increased by fine-tuning its hyperparameters using TALA, where TALA is developed by incorporating the Taylor series [6] with ALA [15]. The process executed during spectrum sensing is briefly exemplified as follows,

4.2.1. Architecture of DNN

DNN [14] is a type of convolutional network, which comprises multiple non-linear layers, such as multiple neural nets and hidden layers. Backpropagation is executed in DNN for identifying the output variables while training the cyclostationary feature N_l^{SCF} . The DNN also helps to showcase the correlation of the system based on its nonlinearity and complexity. The DNN significantly learn the complex nonlinear patterns from the signal spectrum and generalizes the unseen channel conditions for making it suitable for uncertain and dynamic spectrum conditions.

Assume the DNN with a tuple $B=(r,s,t)$, where t indicates a set of functions, r is the set of layers, and $s \subseteq r \times r$ represents a set of connections among the layers. Let us consider the layer among the input and output layer is given by the hidden layer, C_n the output layer, and r_1 the input layer. Also, the w^{th} node of a^{th} layer is signified as $k_{a,w}$, and each layer r_a consists m_a neurons. For $1 \le w \le m_a$ and $1 < a < Q$, each node $k_{a,w}$ is associated with two variables $u_{a,w}$ and $v_{a,w}$ for recording the values of the activation function. Here, the Rectified Linear Unit (ReLU) is utilized as an activation function, and the activation value of hidden layers is designated as,

$$v_{a,w} = \mathrm{Re}\,LU\left(u_{a,w}\right) = \begin{cases} u_{a,w} & \mathit{if}\ u_{a,w} \ge o \\ 0 & \mathit{Otherwise} \end{cases} \tag{10}$$

For $1 \le x \le p_1$, each input node $k_{1,w}$ is associated with a variable $v_{1,w}$, and for $1 < a < m_a$, each output node $k_{Q,w}$ is associated with a variable $u_{Q,w}$ due to no activation functions. Consider, $v_{a,w}$ be the one dimension for each variable, $t \in X_{r_1}$ signifies the input at every point, and X_{r_a} be the vector space associated with the layer r_a . Further, the nodes are interconnected with preceeding layer by pre-trained parameters with $1 \le w \le m_a$ and $2 \le a \le Q$ for all a and w , and is expressed by,

$$u_{a,w} = I_{a,w} + \sum_{1 \le z \le m_{a-1}} C_{a-1,z,w} . v_{a-1,s} \tag{11}$$

In the expression, $I_{a,w}$ signifies the bias of node $k_{a,w}$ and $C_{a-1,z,w}$ is the weight for connecting $k_{a,w}$ and $k_{a-1,w}$. As ReLU is used as the activation function, the neural network has a nonlinear characteristic. Finally, DNN assign labels and the assigned label is designated as,

$$S_S = \arg\max_{1 \le w \le m_Q u_{Q,w}} \tag{12}$$

here, the resultant output of DNN obtained from cyclostationary feature N_l^{SCF} is signified as S_S , where the architecture of DNN is displayed in Fig. 3.

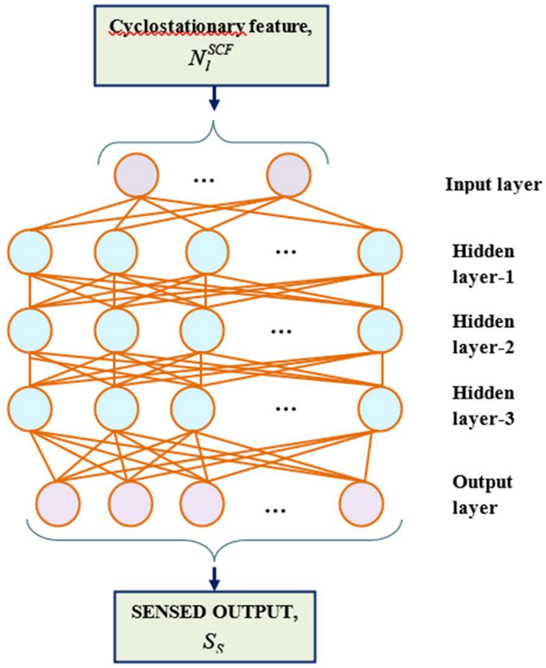


Fig. 3. *Architecture of DNN*

4.2.2. Designed TALA for Training DNN

The sensing performance of the DNN model is enhanced by training hyperparameters using TALA. Here, the TALA is designed by integrating the Taylor series [6] with ALA [15]. A bio-inspired metaheuristic algorithm, called ALA, is designed considering the distinct characterise of lemmings in nature. These behaviors include social coordination, adaptive navigation, and instinctive responses to environmental threats, which are mathematically translated into search strategies. The ALA is mathematically modelled by following evading and foraging predators, digging holes, and long-distance migration characters. The ALA attained high stability and convergence speed to robustly converge on the global solution and evade local optima in the global search space. Its ability to balance exploration and exploitation enables it to perform well across complex, multimodal optimization landscapes, which are typical in deep learning hyperparameter spaces. Taylor series, a linear statistical technique, is used to predict future values by estimating the time series data. Taylor series is considered an autoregressive statistical model that approximates the local characteristics of a function. In this context, Taylor series enhances the local search capability by providing fine-grained approximations near candidate solutions, which guides the search agents more precisely. The integration of ALA with Taylor series helps to perform a better exploitation process and to increase the convergence rate near the optima. The TALA is mathematically modelled as follows,

Step 1: Initialization

The lemmings' position is initialized in the population-based algorithm, and the optimal solution is obtained based on the optimal position in each iteration. Thus, the initial candidate solution in matrix format is designated as,

$$G=\begin{bmatrix} g_{1,1} & g_{1,2} & \cdots & g_{1,x-1} & g_{1,x} \\ g_{2,1} & g_{2,2} & \cdots & g_{2,x-1} & g_{1,x} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ g_{c-1,1} & g_{c-1,2} & \cdots & g_{c-1,x-1} & g_{c-1,x} \\ g_{c,1} & g_{c,2} & \cdots & g_{c,x-1} & g_{c,x} \end{bmatrix} \tag{13}$$

$$g_{m,n}=\kappa_m+Rand\times\left(\lambda_m-\kappa_m\right),\quad m=1,2,3,...,c,\quad n=1,2,3,...,x \tag{14}$$

In the expression, the upper and lower limits of the dimension are signified as λ_m and κ_m, the random value set to 0 to 1 is given by $Rand$. Moreover, the total dimensions are represented as x the population size is signified as c, and G is the matrix of the initial candidate solution set.

Step 2: Fitness computation

The best candidate solution is identified by MSE as fitness, and the minimum fitness function is deemed the ideal solution. The MSE is designated as,

$$MSE = \frac{1}{Y}\sum_{c=0}^{Y}\left(S_{S_c}^{*} - S_{S_c}\right)^2 \tag{15}$$

where the expected output of DNN is given as $S_{S_c}^{*}$, the sensed output of DNN is symbolized as S_{S_c}, and the total training samples are represented as Y.

Step 3: Exploration

The exploration process of lemmings is performed based on two distinct characteristics, namely digging holes and long-distance migration. The process executed in the modelling of the two behaviours is briefly delineated as follows,

When the food is scarce, the long-distance migration is performed by the lemmings because of overpopulation. The lemmings move over the search space to identify habitats with more food sources to get more resources and better living conditions based on the random individual's position and the current position in the population. Thus, the long-distance migration behaviour executed by lemmings is demonstrated as follows,

$$G_m(p+1) = G_{BEST}(p) + \chi \times \eta \times \left(U \times \left(G_{BEST}(p) - G_m(p)\right) + (1-U) \times \left(G_m(p) - G_n(p)\right)\right) \tag{16}$$

Here, the random number that characterizes Brownian motion is signified as η, the flag used for changing search direction is given by χ, the present optimal location is represented as $G_{BEST}(p)$, and the m^{th} search agent's location at $(p+1)^{th}$ iteration is symbolized as $G_m(p+1)$. Moreover, the randomly selected individual from the population is denoted as $G_n(p)$ and the vector of uniformly distributed random numbers between [-1,1] is specified as U.

Digging burrows is the second characteristic of lemmings, where complex tunnels are constructed by lemmings as their habitat and for storing food and providing secure shelters. Usually, new burrows are randomly dug by lemmings based on the random individuals in the population and present burrow locations. This helps to effectively search for food and quickly escape the threats of predators. The digging behaviour is expressed as,

$$G_m(p+1) = G_m(p) + \chi \times \rho \times \left(G_{BEST}(p) - G_o(p)\right) \tag{17}$$

where the randomly selected search individual is expressed as $G_o(p)$, and the random number considering the number of iterations is given by ρ.

The Taylor series [6] is integrated with ALA [15] to execute a better exploitation process and to enhance the convergence rate near optima. From Taylor,

$$G_m(p+1) = \frac{G_m'(p)}{1!} + \frac{G_m''(p)}{2!} \tag{18}$$

$$G_m'(p) = \frac{G_m(p) - G_m(p-f)}{f}, \quad G_m''(p) = \frac{G_m(p) - 2G_m(p-f) + G_m(p-2f)}{f^2} \tag{19}$$

In the expression, f is the expansion point of the series.

Assume $f = 1$, then equations (18) and (19) can be written as,

$$G_m(p+1) = \frac{G_m(p) - G_m(p-1)}{1!} + \frac{G_m(p) - 2G_m(p-1) + G_m(p-2)}{2!} \tag{20}$$

$$G_m(p+1) = G_m(p)\left[1+1+\frac{1}{2}\right] - G_m(p-1) - \frac{2G_m(p-1)}{2} + \frac{G_m(p-2)}{2} \tag{21}$$

$$G_m(p+1) = G_m(p)\frac{5}{2} - 2G_m(p-1) - \frac{G_m(p-2)}{2} \tag{22}$$

$$G_m(p) = \frac{2}{5}\left[G_m(p+1) - 2G_m(p-1) - \frac{G_m(p-2)}{2}\right] \tag{23}$$

Substituting equation (23) in equation (17),

$$G_m(p+1) = \frac{2}{5}\left[G_m(p+1) - 2G_m(p-1) - \frac{G_m(p-2)}{2}\right] + \chi \times \rho \times \left(G_{BEST}(p) - G_o(p)\right) \tag{24}$$

$$\frac{G_m(p+1) * 5 - 2G_m(p+1)}{5} = \frac{5\left[\chi \times \rho \times \left(G_{BEST}(p) - G_o(p)\right)\right] - 2\left[2G_m(p-1) - G_m(p-2)\right]}{5} \tag{25}$$

$$G_m(p+1)[5-2] = 5\left[\chi \times \rho \times \left(G_{BEST}(p) - G_o(p)\right)\right] - 4G_m(p-1) + G_m(p-2) \tag{26}$$

Hence, the updated expression of TALA is expressed as,

$$G_m(p+1)=\frac{1}{3}\Big[5\big[\chi\times\rho\times\big(G_{BEST}(p)-G_o(p)\big)\big]-4G_m(p-1)+G_m(p-2)\Big] \tag{27}$$

Step 4: Exploitation

In the exploitation phase, the lemmings move arbitrarily and widely using their keen sense of hearing and smell towards burrows for the location of food sources. This behavior is metaphorically modeled to guide search agents towards promising regions in the solution space once initial exploration has identified potential optima. Generally, a small foraging area is established by the lemmings within their habitat, considering the availability of food sources. This behavior is translated into a local search mechanism in the algorithm, where solution candidates intensify their search around high-fitness regions to refine the results. Hence, the lemmings follow random foraging characteristics based on a spiral wrapping mechanism, and this is modeled as,

$$G_m(p+1)=G_{BEST}(p)+\chi\times\varpi\times Rand\times G_m(p) \tag{28}$$

Here, the spiral shape of the random search is signified as ϖ .

Furthermore, the lemmings follow protective and avoidance characteristics while encountering danger. At this time, the burrow becomes the main refuge for lemmings, where the lemmings flee to the burrow by utilizing their exceptional running ability once the enemies are detected. Likewise, deceptive manoeuvres are followed by lemmings to evade the pursuit by predators. Thus, the evading natural predator behaviour performed by lemmings is designated as,

$$G_m(p+1)=G_{BEST}(p)+\chi\times V\times Levy(x)\times\big(G_{BEST}(p)-G_m(p)\big) \tag{30}$$

where $Levy(.)$ represents the Levy flight function, and the lemmings' escape coefficient is given by V .

Step 5: Fitness re-estimation

Equation (15) is utilized for the estimation of the optimal solution, where the generated solution can be replaced if any solutions are determined to be superior to the current solution.

Step 6: Termination

The algorithmic steps of TALA are repeated until attaining best candidate solutions are attained.

5. Results and Discussion

The analysis executed for investigating the efficacy of TALA_DNN in spectrum sensing is demonstrated as follows.

5.1. Experimental set-up

The TALA_DNN for spectrum sensing is executed using a Python tool with simulation.

5.2. Performance Measures

To investigate the efficacy of TALA_DNN, different evaluation indicators are used, and they are illustrated below,

Probability of detection: It is the likelihood of CRN in correctly detecting the availability of PUs in the given frequency band for avoiding interference.

Computational time: The time taken by the TALA_DNN model to perform the spectrum sensing task in CRN is called computational time.

Probability of false alarm: The probability of falsely detecting a PU in the spectrum when the PU is not available is termed the probability of false alarm.

5.3. Comparative Techniques

The supremacy of TALA_DNN is investigated by comparing it with prevailing schemes, like STFT-RADN [1], FOM(CS-GWO) [2], CNN [4], and the 3EED spectrum sensing algorithm [5].

5.4. Comparative Assessment

In order to quantitatively validate the supremacy of TALA_DNN in spectrum sensing, the investigation is performed by varying the number of users. The analyses executed are delineated as follows.

5.4.1. Analysis of TALA_DNN for 100 users

In Fig. 4, the investigation of TALA_DNN used for spectrum sensing in CRN with 100 users concerning SNR is demonstrated. The analysis of TALA_DNN using the probability of false alarm by altering SNR is elucidated in Fig. 4(a). The TALA_DNN recorded a probability of false alarm of 5.83×10^{-5} for SNR of 30 dB, whereas the probability of false alarm observed by baseline models, like STFT-RADN, FOM(CS-GWO), CNN, and 3EED spectrum sensing algorithm is 5.22×10^{-3}, 1.17×10^{-3}, 2.61×10^{-4}, and 1.23×10^{-4}. This confirms that TALA-DNN substantially minimizes incorrect detections, ensuring better spectrum utilization without interfering with PUs. Fig. 4(b) depicts the investigation of TALA_DNN using the probability of detection. Here, the TALA_DNN observed a probability of detection of 0.9999 for SNR of 30 dB, where the existing works recorded a probability of detection of 0.9948 by STFT-RADN, 0.9988 by FOM(CS-GWO), 0.9991 by CNN, and 0.9995 by 3EED spectrum sensing algorithm. This indicates that TALA-DNN is highly effective in correctly identifying occupied spectrum, even under high-user density scenarios. Further, the evaluation of TALA_DNN using computational time is examined in Fig. 4(c). The analysis elucidates that the computational time of 0.199 sec is recorded by TALA_DNN at SNR of 30 dB, and the computational time measured by baseline models, like STFT-RADN, is 0.409 sec, FOM(CS-GWO) is 0.378 sec, CNN is 0.327 sec, and the 3EED spectrum sensing algorithm is 0.258 sec. The reduced computational load of TALA-DNN highlights its suitability for real-time CRN applications, where latency is critical.

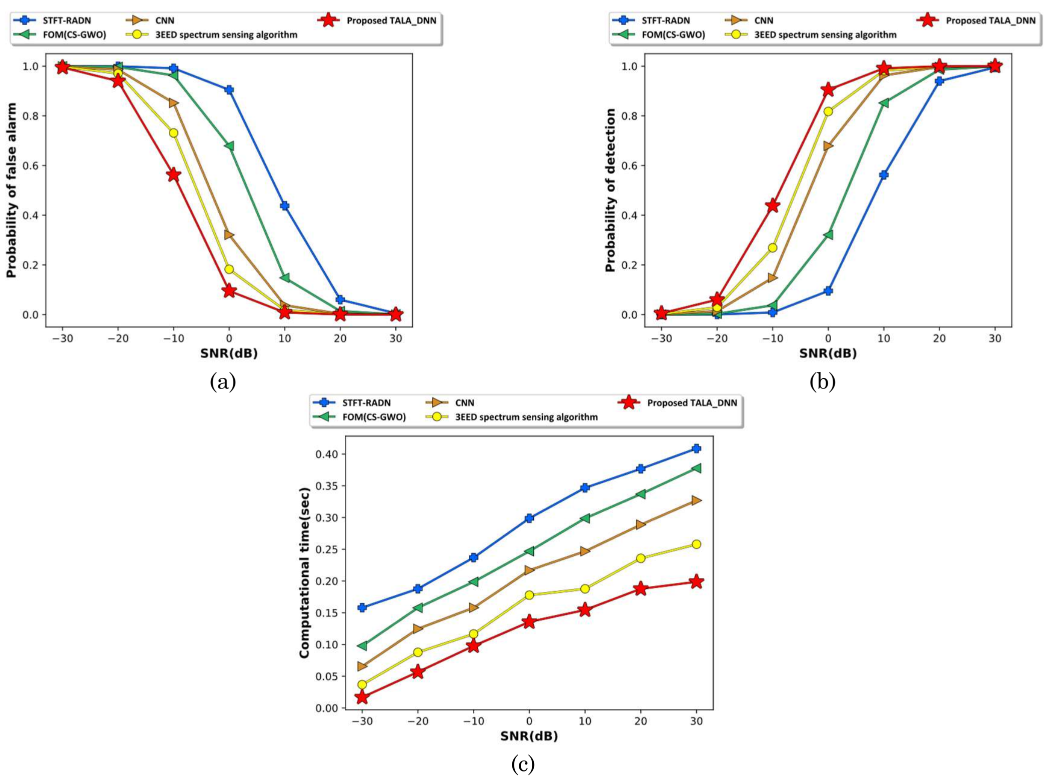
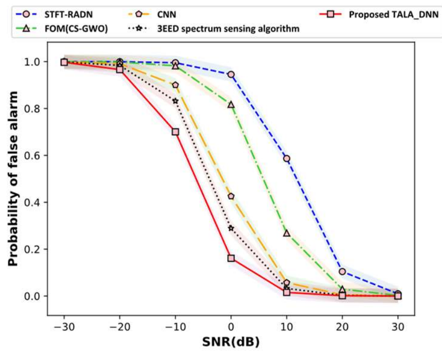


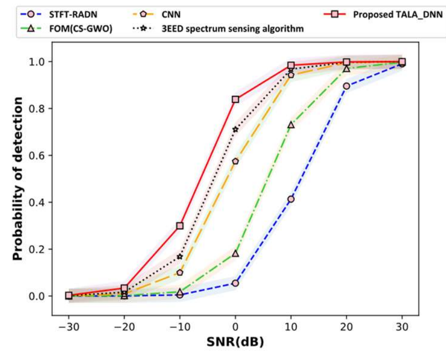
Fig. 4. *Investigation of TALA_DNN using (a) Probability of false alarm, (b) Probability of detection, (c) computational time for 100 users*

5.4.2. Analysis of TALA_DNN for 200 users

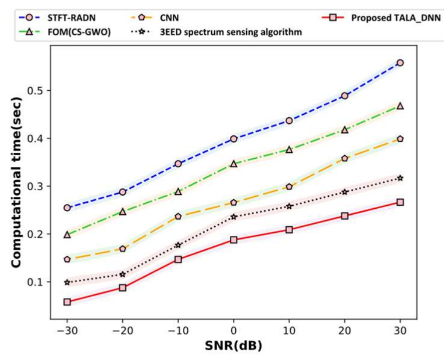
The valuation of TALA_DNN designed for spectrum sensing in CRN based on SNR concerning 200 users is given in Fig. 5. The investigation of TALA_DNN utilizing the probability of false alarm considering SNR is depicted in Fig. 5(a). Here, the TALA_DNN recorded a probability of false alarm of 1.06×10^{-4} for SNR of 30 dB, and the existing works recorded a probability of false alarm of 9.47×10^{-3} by STFT-RADN, 2.47×10^{-3} by FOM(CS-GWO), 4.1×10^{-4} by CNN, and 2.25×10^{-4} by 3EED spectrum sensing algorithm. This showcases TALA-DNN's improved accuracy in correctly identifying idle channels, which is crucial for preventing interference in dense CRN environments. The analysis of TALA_DNN using the probability of detection based on SNR is shown in Fig. 5(b). The analysis demonstrates that the probability of detection of 0.9998 is attained by TALA_DNN with the SNR of 30 dB, where the probability of detection recorded by baseline techniques, such as STFT-RADN, is 0.9905, FOM(CS-GWO) is 0.9975, CNN is 0.9996, and the 3EED spectrum sensing algorithm is 0.9997. This reflects the model's strong capability to detect the presence of PUs with near-perfect accuracy, even when the network becomes more congested. Moreover, the analysis of TALA_DNN using computational time altering SNR is portrayed in Fig. 5(c). The TALA_DNN measured computational time of 0.267 sec for SNR of 30 dB, whereas the computational time observed by existing models, like STFT-RADN, FOM(CS-GWO), CNN, and 3EED spectrum sensing algorithm is 0.558 sec, 0.468 sec, 0.399 sec, and 0.317 sec. The results demonstrate that TALA-DNN remains computationally efficient as user count increases, which is essential for real-time spectrum sensing in scalable CRN deployments.



(a)



(b)



(c)

Fig. 5. *Investigation of TALA_DNN using (a) Probability of false alarm, (b) Probability of detection, (c) computational time for 200 users*

5.5. Comparative Discussion

The outcomes measured by TALA_DNN and previous works used for spectrum sensing in CRN with 100 and 200 users are illustrated in Table 1. The TALA_DNN attained superior performance compared to existing schemes with probability of false alarm, probability of detection, and computational time of 5.83×10^{-5}, 0.9999, and 0.199 sec for SNR of 30 dB. This significant enhancement indicates the model's capability to handle high-noise environments while maintaining detection precision. Similarly, the probability of false alarm observed by previous models, like STFT-RADN, FOM(CS-GWO), CNN, and 3EED spectrum sensing algorithm is 5.22×10^{-3}, 1.17×10^{-3}, 2.61×10^{-4}, and 1.23×10^{-4}. These figures clearly show that while earlier models offered incremental improvements, they could not match the ultra-low false alarm rate achieved by TALA-DNN. The existing works recorded probability of detection of 0.9948 by STFT-RADN, 0.9988 by FOM(CS-GWO), 0.9991 by CNN, and 0.9995 by the 3EED spectrum sensing algorithm. Despite their competitive performance, these models lack the generalization strength observed in TALA-DNN across varying user densities and SNR levels. Also, the computational time measured by baseline models, like STFT-RADN, is 0.409 sec, FOM(CS-GWO) is 0.378 sec, CNN is 0.327 sec, and the 3EED spectrum sensing algorithm is 0.258 sec. This demonstrates that although earlier approaches attempted to minimize detection time, they were not optimized for real-time adaptability in dynamic spectrum environments. Overall, the results show that the TALA_DNN outperforms previous works in spectrum sensing. As evidenced, the TALA_DNN effectively learned the complex nonlinear patterns in the signal spectrum compared to prevailing sensing schemes. Its architecture, built upon the Taylor series-based optimization, allows for a finer representation of signal features and enhanced learning of temporal variations. This results in a high probability of detection and a minimum probability of false alarm. Such performance gains are particularly valuable in CRNs where detection accuracy directly affects spectral utilization efficiency. Furthermore, the unseen channel conditions and environment are generalized by TALA_DNN, making it suitable for uncertain and dynamic spectrum conditions.

Table 1. *Comparative discussion*

Evaluation measured	Spectrum sensing techniques				
	STFT-RADN	**FOM(CS-GWO)**	**CNN**	**3EED spectrum sensing algorithm**	**Proposed TALA_DNN**
	For 100 users				
Probability of false alarm	$5.22\text{x}10^{-3}$	$1.17\text{x}10^{-3}$	$2.61\text{x}10^{-4}$	$1.23\text{x}10^{-4}$	***$5.83\text{x}10^{-5}$***
Probability of detection	0.9948	0.9988	0.9991	0.9995	***0.9999***
Computational time (sec)	0.409	0.378	0.327	0.258	***0.199***
	For 200 users				
Probability of false alarm	$9.47\text{x}10^{-3}$	$2.47\text{x}10^{-3}$	$4.1\text{x}10^{-4}$	$2.25\text{x}10^{-4}$	$1.06\text{x}10^{-4}$
Probability of detection	0.9905	0.9975	0.9996	0.9998	0.9998
Computational time (sec)	0.558	0.468	0.399	0.317	0.267

6. Conclusion

Nowadays, spectrum sensing is used to observe the activities of PUs in CRN. Various spectrum sensing methods are used for detecting the activity of the PU without any prior knowledge. Meanwhile, these methods did not ensure the desired performance, and this results in low utilization of spectrum resources. Traditional approaches often suffer from limited adaptability in dynamic or noisy spectrum environments, leading to increased false alarms or missed detections. To address this, the TALA_DNN is designed for spectrum sensing in CRN. The system model of CRN is initially taken under consideration, and then, the signal received from CRN is applied to the cyclic spectrum for extracting the hidden periodicities. This process enhances the signal representation by revealing key modulation patterns that are typically masked in noisy or overlapping frequency bands. Following this, the spectrum sensing is finally executed by DNN, and the performance of DNN is increased by optimally adjusting the hyperparameters using TALA. By integrating Taylor series-based optimization with the lemming-inspired search behavior of ALA, the TALA component ensures faster convergence and avoids local optima, leading to better training outcomes. In addition to this, various experiments are conducted to investigate the efficacy of TALA_DNN in spectrum sensing. The experimental outcomes showcase that the TALA_DNN attained superior performance in spectrum sensing with a probability of false alarm, computational time, and probability of detection of $5.83\text{x}10^{-5}$, 0.199 sec, and 0.9999. Compared to benchmark models, TALA-DNN not only delivers higher accuracy but also offers enhanced generalization across varying SNR levels and user densities, making it suitable for real-time CRN applications. In the future, the efficiency of spectrum sensing in CRN can be enhanced using hybrid deep learning techniques.

Compliance With Ethical Standards

Conflicts of interest: Authors declared that they have no conflict of interest.

Human participants: The conducted research follows ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

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