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Resource Optimization of Cognitive Radio Sensor Network Using Hybrid Metaheuristic Optimization and Machine Learning Algorithms

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ABSTRACT

Cognitive radio sensor networks (CRSNs) are characterized by their ability to adapt to dynamic spectrum availability. Computation power in cognitive radio network (CRN) is essential for efficient spectrum utilization and seamless connectivity among nodes in a sensor-based health monitoring system. The proposed algorithm, Cognitive Adaptive Metaheuristic Optimization Algorithm (CAMOA) is a Hybrid Particle Swarm-Tabu Search Optimization (HPSTSO) technique that integrates two optimization methods: Particle Swarm Optimization (PSO) and Tabu Search (TS). It dynamically selects the best resource allocation algorithm based on the healthcare network requirements of quality of service and channel conditions, traffic load, and network topology to enhance the performance of communication, and contribute to optimal allocation, and maximize resource productivity in resource-constrained CRSNs. The evaluation metrics are recorded and exported into a newly created dataset named Cognitive Adaptive Metaheuristic Optimization Dataset (CAMOD.csv), which is used to train a machine learning model as Multilayer Perceptron (MLP) neural network—to provide the best prediction of spectrum sensing of secondary users with consideration resource utilization for each cognitive radio sensor node. Results of HPSTSO showed that the average of processing time compared to existing approaches is 30.0675 seconds, packet delivery ratio is 99.08%, channel utilization is 99.166%, probability of channel collision is 0.0508, total network utilization is 7.0604 KB and total resource utilization is 23.0871%. In addition, the MLP accuracy of RadioML2016.10B dataset compared to existing approaches is 98.7%, Precision is 99.98%, Recall is 95.76% and F1 Score is 97.82%. Furthermore, MLP accuracy, precision, recall and F1 score of the CAMOD dataset are 99.45%, 1.0, 98.38%, and 99.18% respectively.

1. INTRODUCTION

One of the most important uses of wireless communications technologies is their contribution to supporting a wide range of different applications in the fields of electronic health, which contribute to the transfer of medical data and patient information to the hospital and the medical side [1]. However, the use of wireless communications technology in the fields of medical specialties represents a major challenge, as it can affect the electromagnetic interference caused by these vital devices as a result of their wireless devices, which poses a threat to their performance. In addition, different types of e-health applications have different priorities, so these must be given priority to the wireless channel by the relevant corresponding devices influencing its operation [2].

One of the most important basic requirements in the field of wireless communications service is the availability of radio spectrum, and it is considered a major challenge as the spectrum used in the field of wireless radio is a limited and expensive natural resource, and the tremendous growth of the wireless communications market has led to the scarcity of radio spectrum [3]. As for the remaining part of the spectrum, it is unused or little used. Therefore, there is a need to improve the use of the spectrum, and the ideal choice is dynamic access to the spectrum and defining a cognitive radio network [4].

The principle of operation of cognitive radio networks is to adapt to the surrounding radio environment by relying on the knowledge generated from this environment [5]. They can access the licensed spectrum intelligently, opportunistically, and more efficiently without affecting the licensed spectrum, which improves the general use of the radio spectrum [6]. Cognitive radio networks are based on spectrum sensing to discover vacancies and obtain appropriate use of the spectrum through dynamic access It discovers spectrum gaps efficiently and accesses the spectrum in an optimal, opportunistic manner [7].

One of the important uses of radio-based cognitive wireless communications is emergency networks designed for disaster situations and healthcare systems [8]. It is the nature of the radio system's work and perception and its dealing with channels of the spectrum that are not sufficiently used. It transmits data of various types and media and does not take the access of secondary or low-priority users into account [9]. Cognitive radio in healthcare applications is used in sensitive medical devices that are supposed to be protected from interference as a result of wireless transmissions. They are including incubators, infusion pumps, and pacemakers, as medical devices can transmit data in a representative manner by using wireless signal for example, these devices include telemetry monitoring devices, wireless Holter monitors, and wireless electrocardiogram devices [10]. The data transmission of these active medical devices can be interfered with through wireless transmission, relying on other non-medical devices, such as medical devices and information networks [11].

Since every user in radio networks has access to the radio spectrum, the secondary user does not need to be aware of the presence of the primary user [12]. However, restrictions regarding user interference in protected applications still exist, and prioritization between different users and applications will be required to access the channel. To achieve the best service differentiation [13]. This is through the ability to monitor the spectrum and its characteristics and study the behavior of the node that operates in this spectrum and access it dynamically, as the cognitive radio node allows access to the spectrum and taking into account the quality of service during its different health normalization. It also allows relying on a spectrum or supports the spectrum as an ideal associated channel behavior [14].

Radio resources can then be allocated, such as transmission and reception time periods, specifying frequency bands, transmitting antennas, transmission power, etc., according to the current channel condition. Dynamic resource allocation schemes can rely on these variations in the frequency resources and thus lead to much better performance compared to static resource allocation schemes [15]. In addition, dynamic resource allocation works to resolve conflicts between competing nodes to exploit multiple resources and to ensure achieving fairness and avoiding interference and collisions, as dynamic resource allocation schemes deal efficiently with spectrum movement and take care of the quality-of-service requirements and priorities of different services and different nodes [16].

Besides, artificial intelligence learning technologies have gained many applications in the field of cognitive radio devices, as these technologies aim to make machines perform tasks in a way that resembles experts, such as inference, reasoning, problem-solving, knowledge representation, and learning approaches [17].

The main research problems are the dynamic spectrum allocation, how to ensure the quality of service, increase network life, and ensure the lack of interference between nodes and the network elements, reducing sensing information overhead, as well as computational interference operations which affect primary and secondary users.

The objectives of the proposed system are resource allocation, which results in increasing throughput and maximum resource usage of the entire network, and reduced processing time of sent/received packets. Balancing of the sensed spectrum between multiple sensor nodes, and efficient use of spectrum during the sensing process. Optimally meeting QoS requirements reducing or avoiding interference with the primary user network, and eliminating unnecessary transfers of the spectrum to reduce the overall power consumption, reduce the overall delay, and improve the reliability of transmission.

This paper is organized into several key sections. Section 1 showed the general introduction about cognitive radio sensor network (CRSN) and resource optimization based on Metaheuristic with Machine Learning Algorithms. Section 2 reviewed common related works of the proposed system. Section 3 showed the proposed methodology based on hybrid Particle Swarm Optimization (PSO) and Tabu Search (TS) algorithms as hybrid approach Particle Swarm-Tabu Search Optimization (HPSTSO) for resource allocation in cognitive radio network. Section 4 presented the proposed implementation method based on OMNET++ for network simulation and Java for trained model of MLP machine learning algorithm. Section 5 and Section 6 showed the proposed system results and system comparison. The proposed system is concluded in Section 7.

2. RELATED WORKS

This section represents an overview of the most related works in the field of cognitive radio sensor health monitoring systems, which use different types of metaheuristic optimization algorithms and machine learning algorithms to enhance spectrum sensing and resource allocation.

A throughput in energy-aware harvesting model of cognitive radio network (CRN) is proposed by Bakshi et al. [18] to improve the performance of the energy harvesting process of CRN (EHCRN). The main focus was to find the optimal solution to deal with the problem of maximizing productivity. The proposed method is Rank-Based Multi-Objective Antlion Optimization (RMOALO). The proposed model is illustrated based on five reference mathematical functions and compared to Multi-Objective Particle Swarm Optimization (MOPSO), Multi-Objective Moth Flame Optimization (MOMFO), Multi-Objective Antlion Optimizer (MOALO)-Tournament, and MOALO-Roulette. The results showed RMOALO improvement of average throughput arrived to 16.33% with the optimal value of the sensing duration for a different amount of limited energy compared to MOPSO, MOMFO, MOALO-Roulette, and MOALO-Tournament.

Support Vector Machine-based Red Deer Algorithm (SVM-RDA) based on Spectrum Handoff (SHO) decision-making has been proposed by Srivastava et al. [19] to make the CRN handoff procedure more efficient. The hybrid SVM-RDA and evaluates network metrics such as throughput and the number of failed transmissions and receptions. This approach allows the secondary user to move to a channel that is not previously occupied, thus reducing failures during the connection. This hybrid handover technology ensures that accurate predictive techniques are produced by examining all possible outcomes even when the execution environment is unknown. The results showed that the SVM-RDA is flexible and does not require any complexity to implement. This study presented improved system performance during the spectrum handover process. The inferred technique predicts delivery delays and reduces delivery numbers. The results also show that the adopted method is the best in making predictions with a smaller number of deliveries compared to other related methods.

Energy efficiency design techniques have been used by Eappen and Shankar [20] for various spectrum sensing scenarios to solve the problem of improving efficiency and detecting spectrum holes while improving energy utilization using Particle Swarm Optimization (PSO) and Gravitational Search Algorithm (GSA) called hybrid PSO-GSA. From the new hybridization of the proposed system, it is possible to achieve a balanced trade-off between exploration and exploitation capabilities and to efficiently integrate the mutation and crossover factor to discover spectrum openings using improved values of transmission power, sensing bandwidth, and power spectral density, thus improving the efficiency of energy use in sensing the radio spectrum. The simulation results demonstrated the efficiency of the proposed system in improving the energy efficiency of spectrum sensing in terms of transmission capacity, spectrum sensing bandwidth, and power spectral density compared to the PSO or Artificial Bee Colony (ABC) algorithm. The results of the proposed algorithm showed that it is effective in the field of spectrum sensing compared to other algorithms, as it obtained optimal energy efficiency during spectral sensing.

An algorithm for channel allocation in cognitive radio networks has been proposed by Latif et al. [21] represented by the evolutionary optimization algorithm. The proposed method consists of PSO as Differential Evolution-Based Particle Swarm Optimization with the Repair Process (DEPSO-RP). As a sign of this, the system proposed fixing conflicts between the secondary cognitive network units to increase spectrum allocation in the network. The performance of the algorithm was also evaluated through a large-scale simulation process. The results showed that the spectrum allocation process had better performance concerning the channel compared to other existing algorithms. The results showed that the proposed algorithm converged. With the results of the best solutions much faster than other algorithms, it combines the good characteristics of the PSO or Differential Evolution (DE) algorithm.

A cooperative spectrum sensing of CRNs is implemented with the Machine Learning model by Tavares et al. [22] to enhance spectrum sensing based on a statistical analysis of the energy detection model. It is based on deriving the probability of detection and false alarm based on the number of samples and the Signal to Noise Ratio (SNR) ratio for Secondary Users (SUs), where the channel exploitation detection is obtained from analytical techniques such as AND/OR. The used ML algorithms are Multilayer Perceptron (MLP), Support Vector Machine (SVM), and Naive Bayes (NB), depending on the operating characteristics of the receiver and the Area Under the Curve (AUC) scales. Using standard development tools, the performance of the cloud models was obtained. The results demonstrated that the proposed algorithm provided an optimal range between the training time and the channel discovery performance.

An opportunistic routing that contributes to increasing the efficiency and reliability of cognitive radio networks has been proposed by Abdullah et al. [23]. They addressed the issue of delay and degradation of the packet delivery rate, taking into account the network's frequency cleanliness and throughput. They used the Hybrid Firefly and Grey-Wolf Optimization-based Spectrum Map-Empowered Opportunistic Routing (SMOR) (HFGWOSMOR) to improve performance by analyzing the relationship between delay and throughput. A set of cooperative multi-path connections were created between cognitive nodes and the energy values of the received signals were calculated during routing to be within the bandwidth and time thresholds, as well as dealing with performance issues according to user requirements. The results showed that the proposed system works efficiently in opportunistic routing compared to other models.

Multi-channel path scheduling is proposed by Dasari and Venkatram [24] due to the difficulty of communication and spectrum utilization due to the climatic effects of radio signal. A multi-channel path scheduling optimization system is proposed to systematically enhance network performance and reliability for various scheduling problems. The path is scheduled effectively and accurately to increase the packet delivery ratio, spectrum utilization, reduce interference level and increase energy efficiency. The Optimizing Multichannel Path Scheduling (OMPS) model is proposed as it shows a reduction in access time for real-time applications, improve spectrum efficiency, reduce channel interference and increase throughput. The results show network performance enhancement that a variety of multi-channel path scheduling is simulated according to the network evaluation parameters.

Spectrum sensing in cognitive radio requires an analytical approach based on data due to the inaccuracy of data in advanced wireless radio networks. A deep architecture as Primary User-Detection Network (PU-DetNet) was proposed by Soni et al. [25] that detects the primary user and decodes both the analytical approach and the data-based approach. The system is based on a description of a technique that reduces the computation of the inference time and the number of interval operations, as it involves linking the loss function so that each layer of the proposed architecture has its own loss function, and this function is improved during training the system. The results showed a signal-to-noise ratio of 10 dB, and the primary user detection rate for the Long Short Term Memory (LSTM) algorithm reached 39% and 56%, and the CNN between 45% and 84%, and the Artificial Neural Network (ANN) algorithm was 53% and 128%. The best accuracy of the proposed system was superior by ANN as 93.15%, and the throughput improved by 69.52% of ANN compared to other models.

The proposed system contributions are the signal-to-noise ratio witnessed improvements in the quality of the data transmission signal with less interference, which improves the effective use of the spectrum, as well as the optimal allocation of resources in the network in the hybrid system, which led to a decrease in channel collisions and interruptions during erection, as resources were allocated effectively and efficiently, which contributed to maximizing productivity in the cognitive radio network, especially in health monitoring systems, where reliability and speed of transmission are Data is very important.

3. THE PROPOSED METHODOLOGY

The proposed system employed an HPSTSO for resource allocation, utilizing two optimization methods as an adaptive Metahuristic approach PSO and TS algorithms. The PSO has been applied to CRNs to optimize spectrum allocation, power control, and other resource allocation problems. Besides, TS has been used in CRNs to optimize spectrum allocation, channel assignment, and other resource allocation tasks.

3.1 PSO

This algorithm is implemented to optimize and manage network resources within the Fusion Center (FC), which allows dynamic adaptation to different network conditions to improve resource allocation based on recent evaluations of network performance metrics. The steps to implement this algorithm are as follows: The first step is to determine the number of particles represented by secondary users and to know their locations and their movement speed randomly within the spectrum limits of the network. The second step is to evaluate the fitness of each body based on a function that takes into account the spectrum usage, efficiency, and quality of service metrics for each secondary user. The third step is to compare the current fitness of each secondary user to determine the best node to receive data and fix the best position for this node. The fourth step is to update the speed for each secondary user based on inertia and perception. The fourth step is to repeat the evaluation and update steps until obtaining the best node that contributes to allocating resources and using them to find the output results as the optimal solution for allocating resources to secondary users in the network by coordinating between the FC and secondary users. The used PSO based on the population size is 25 particles, inertia weight is 0.5 and coefficients is 1.5.

3.2 TS

This algorithm was implemented in the Cognitive radio network FC to facilitate cooperation between secondary users and the FC. The steps for implementing this algorithm are as follows:

Step 1: Initialization, which is based on determining the initial solution for allocating resources based on spectrum bands and user assignments and finding solutions to avoid redirecting data to the same node.

Step 2: Finding solutions for allocating resources by making adjustments to the characteristics of spectrum bands between secondary users.

Step 3: Evaluate the suitability of solutions for all nodes participating with the FC, taking into account productivity, interference levels, and quality of service for each secondary user.

Step 4: Select the best node based on performance evaluation and ensure that it is not in the prohibited list for nodes that do not respond to resource allocation.

Step 5: Continuous updating of the transition between nodes to choose the best oldest suitable one to respond to the FC.

Step 6: Outputting the best solution found to allocate optimal resources to secondary users. The used Tabu Search Parameters based on the length of the tabu list is 10% of the solution space size, total number of iterations is 20 and candidate set size of around 10.

3.3 HPSTSO

The HPSTSO model is applied and configured in the central point node as a FC to provide head management for all Secondary Users (SUs) nodes. The FC works based on collecting spectrum sensing information from SUs nodes across the network. It used this spectrum sensing information to enhance allocating spectrum bands and mitigate interference dynamically according to SUs requirements and availability.

The main objective of the collaboration between the FC and the secondary users is to share the spectrum sensing data and performance metrics of each secondary user with the FC, which allows it to make clear central decisions after collecting information from the secondary users to evaluate and improve resource allocation strategies collectively. The FC provides feedback on the resource allocation performance of each secondary user and thus contributes to modifying their operations based on the knowledge generated from this information. It dynamically adapts to the evolution of network conditions, which enhances the overall network efficiency and improves resource allocation while minimizing interference and maximizing the quality of communication between secondary users.

Pseudocode of the proposed HPSTSO algorithm

```
1-      Initialize parameters:
   number_of_SUs, dimensions, bounds
   max_iterations, PSTSO_list_size
2-      Initialize SUs:
   For each SU i do
      Randomly initialize position x[i] and velocity v[i]
      Set personal_best_position[i] = x[i]
      Set personal_best_fitness[i] = evaluate_fitness(x[i])
   EndFor
3-      Initialize global_best_position and global_best_fitness
Set up empty PSTSO list
While iteration < max_iterations do
   For each SU i do
      Update velocity v[i]
      Update position x[i] using v[i]
 If evaluate_fitness(x[i]) < personal_best_fitness[i] then
         Update personal_best_position[i]
         Update personal_best_fitness[i]
      EndIf
      If personal_best_fitness[i] < global_best_fitness then
         Update global_best_position
         Update global_best_fitness
      EndIf
   EndFor
   For each SU i do
      Generate neighborhood solutions based on x[i]
      For each neighbor solution do
         If neighbor is not in PSTSO list then
            Evaluate fitness of neighbor solution
            If fitness is better than current solution then
               Move to neighbor solution and update PSTSO list
               Add current solution to PSTSO list with size limit
            EndIf
         EndIf
      EndFor
   EndFor
   Update iteration count
EndWhile
4-      Output global_best_position as optimal resource allocation solution
```

The proposed system is based on an adaptive Cognitive Adaptive Metaheuristic Optimization Algorithm (CAMOA) model to allocate network and device resources and share the best channel of spectrum sensing among secondary users. The collected network behavior is registered during the running time of the network topology. Reading of Cognitive Radio (CR) nodes are stored in the dataset and then passed into the learning model to predict primary user absence or appearance during secondary user channel allocation to eliminate interference and ensure that the secondary user is not harmful to the primary user in addition to decreasing a total number of sensing packets which effects on resources and consuming network lifetime. In addition, the architecture of the cognitive radio sensor health monitoring system is secondary users, base station nodes with network devices such as routers or access points and primary users.

In addition, FC decreases the sensing information of primary users generated in each SUs by providing an optimal channel to share with all SUs in the network using a cooperative spectrum sensing technique. Spectrum sensing information collected by FC and exported into the CAMOD.csv dataset is represented in Table 1.

Table 1. Spectrum sensing information attributes of CAMOD dataset

Spectrum Sensing Metric	Description	Purpose
Channel Bandwidth	It represents the channel width used for communication between the receiving and sending nodes in megahertz.	Evaluating the effect of the channel bandwidth on the spectrum sensing performance and data transfer rate.
Received-Signal-Strength (RSS)	The power level of the received signal from each channel. It is represented by −10 dBm to −20 dBm.	To estimate the presence or absence of primary users (PU) nodes.
Spectrum Occupancy	It describes spectrum bands utilized by PUs or SUs. It is represented by 450 to 2700 MHz.	To identify available frequency bands.
Signal to Noise Ratio (SNR)	It is a measure of the ratio of the radio signal strength to the noise strength in the wireless communication channel. It is represented by -10 dB to -20 dB.	Detecting the presence of PUs and enhancing reliable channel quality.
Interference Level	It quantifies the presence of unwanted signals or noise from outside spectrum sources.	To monitor interference levels.
Channel Quality Metrics	Channel Quality attributes are represented by: Channel fading Multipath propagation Channel coherence time	To determine the suitability of communication channel.
Modulation Coding Schemes (MCS)	It is used to transmit data in CRNs. It is represented by: BPSK (Binary Phase Shift Keying) QPSK (Quadrature Phase Shift Keying) 16-QAM (Quadrature Amplitude Modulation)	To optimize spectrum sensing efficiency.
Primary User Activity Metrics	These metrics are represented by: Probability of Detection (Pd) Probability of False Alarm (Pfa) Sensing Time (Ts)	To identify opportunities for spectrum sharing among PUs and SUs.
User Density	Refers to the number of secondary users in a given area, which affects influencing spectrum availability and sensing accuracy.	Analysis of the impact of secondary user density on the performance of spectrum sensing algorithms.

The spectrum sensing information metrics are exported into a CSV dataset file as cognitive radio spectrum sensing information attributes. The CRSSI.csv dataset is tested and evaluated with machine learning methods to enhance the resource allocation of cognitive radio spectrum sensing in the health monitoring system. So, the primary objectives of the Hybrid system under consideration are Decrease Cost, High Scalability, High Flexibility, Maximum Resource Utilization, Decrease Processing Time, Increase Availability and High Throughput. Figure 1 shows the flowchart of the proposed system.

The machine learning model consists of the following steps:

(1) Data gathering from the OMNET ++ simulation environment: Network simulation records are exported into a dataset (CAMOD.csv) file which contains the same attributes from the first stage of resource allocation parameters in Table 1. The system is executed for 60 minutes to record statistics of network evaluation metrics are 16 attributes and the total number of records is about 207993 records.

(2) Preprocessing of collected CAMOD.csv dataset: The pre-processing methods to improve the performance of the proposed multi-layer neural network include several methods that contribute to improving spectrum sensing, as it is important to build an effective data set before training the system, as the following methods include:

A- Data cleaning involves dealing with missing values by removing records that contain missing data or empty values, such as strategies for entering the mean or arithmetic mean to fill in empty records.

B- Measuring features is done by unifying the criteria for normalization features to values within the network parameters used in the dataset, and this is done by applying the minimum and maximum normalization measurement by setting values for measuring features with a fixed range, often between zero and one.

C- Encoding categorical variables by encoding values within categorical attributes by converting them into numeric formats, which is more compatible with the proposed algorithm.

D- The data is divided into a data set, 70% of the training set, 20% of the test set, and 10% of the validation set. The proposed division contributes to the effective evaluation of the model to ensure the highest accuracy in spectrum validation detection.

E- Regularize imbalanced data by applying oversampling techniques from minority classes or under-sampling from the least dominant class to ensure that the model is trained effectively across all data classes.

The trained MLP model was built and evaluated in Java using Eclipse Deeplearning4j for detecting primary user appearance with high accuracy, precision, recall, and F1-score to assess the model's performance. The steps of the experiments using this dataset are shown in Figure 2.

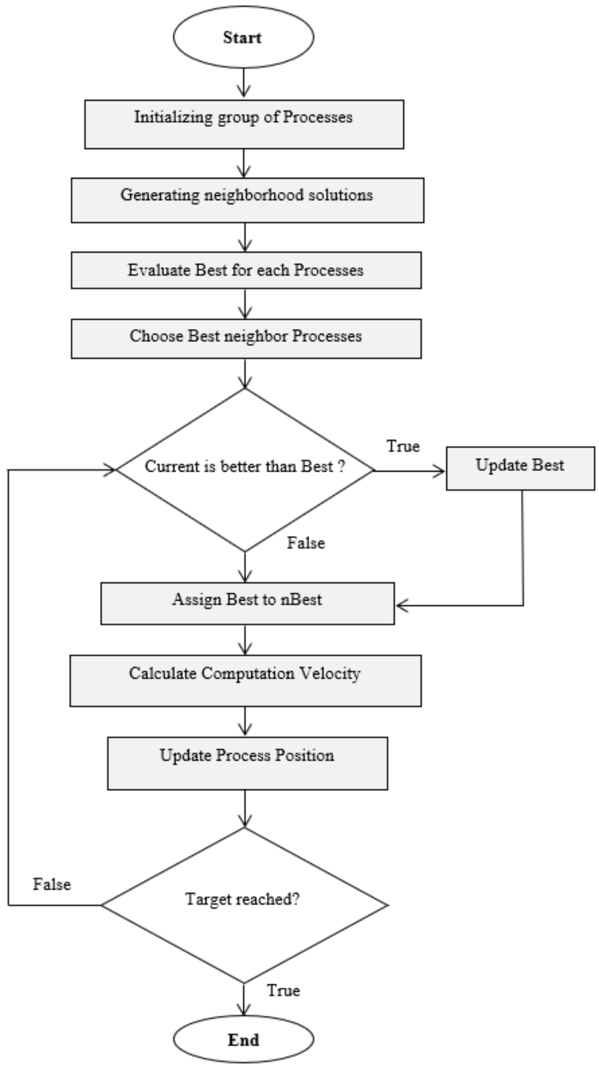

Figure 1. The proposed CAMOA

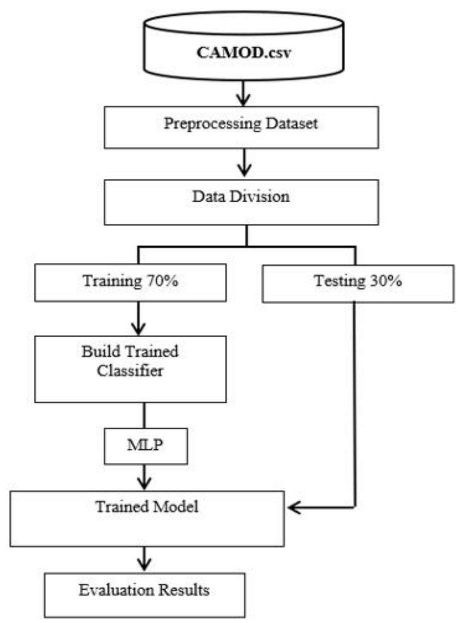

Figure 2. The proposed machine learning algorithm model

The reason for choosing the MLP algorithm over other neural network algorithms is attributed to several factors as strengths of this algorithm, as follows: ease of implementation, as it is relatively simple in construction from connected layers to process the inputs directly, which allows for an easier implementation period and faster training time compared to other more complex algorithms, which makes it suitable for applications with limited resources and require fast decision-making processes. It is also characterized by low demand for processing power without the additional cost associated with building the algorithm, and thus it is quick to respond during the execution of tasks. Furthermore, the MLP algorithm has shown high accuracy when trained in situations where data availability is restricted and linked to the effectiveness of resource management.

Pseudocode of the proposed integration model of CAMOA algorithm and MLP algorithm

```
1-  Initialize MLP parameters:
input_layer_size, hidden layer as number_of_neurons_in_each_hidden_layer and output layer as number_of_classes
2-  Definition objective function as
    evaluate_MLP(params)
3-  Initialize CAMOA parameters

population Initialization P with random hyperparameter sets (learning_rate, batch_size)
fitness evalution P using evaluate_MLP()
    Set p_best and g_best based on fitness
4. Optimization process
While the condition of termination not met do:
    For each individual x in P do
        Cognitive para. updating α and β based on
        network operation performance
        Update position using cognitive learning
        update:
        x_new = x_old + α * (p_best - x_old) + β *
        (g_best - x_old)
        Evaluating new position based on MLP:
         new_fitness = evaluate_MLP(x_new)
      If new_fitness is better than p_best then
            Update p_best with x_new
            If p_best is better than g_best then
               Update g_best with p_best
            End if
      End if
    End For
End While
5. Return optimal g_best parameters for MLP
```

The proposed MLP algorithm is a complementary component of the neural network, as it consists of three separate layers, represented by the input layer, the output layer, and the hidden layer. The proposed model is based on relying on different configurations by changing several hidden layers within the neurons of this algorithm, and the best model to accomplish the specific task is determined, as it is proposed within the system with 20 layers. This algorithm is hidden by performing cross-validation and setting the number of folds to ten folds. This model is based on being the most in-depth method for determining general properties. Use the trained MLP model to predict initial resource allocations based on updated input features derived from the current state of the system with current transmission conditions. MLP model incorporates these predictions into the decision-making processes of Hybrid HPSTSO approach of both PSO and Tabu Search algorithms.

4. THE PROPOSED IMPLEMENTATION

The proposed system is implemented in OMNET ++ to simulate the network architecture of CRSNs and the system is evaluated based on the network evaluator. The outcome of the CRSNs network is a spectrum sensing CAMOD dataset which is then tested based on JAVA programming language to build and execute a machine learning approach. In OMNET++ the health monitoring systems in the cognitive network use different types of data to monitor the patient's health and transfer it effectively from the network, where this data includes the following:

(a) Text data includes information in text format such as patient names, medical history, and information about their health condition.
(b) Image data, where data is transferred in the simulator in the form of images such as X-rays and MRI images for patient analyses.
(c) Video data, which includes a summary of a short video model from monitoring devices that monitor the patient's movement or condition in real-time, which is exchanged between the nodes of the cognitive radio network.
(d) Group of audio files or documents that were captured from special sensors and exchanged in the proposed system, which represents the network inputs that are relied upon during the packet routing process, and then the network is evaluated. Besides, the machine learning approach dataset is based on two datasets:
(e) Own created from the OMNET++ simulation tool as CAMOD dataset. The own created CAMOD dataset is generated from the implementing HPSTSO approach in OMNET++, the dataset attributes of spectrum sensing are Channel Bandwidth, Received-Signal-Strength (RSS), Spectrum Occupancy, Signal to Noise Ratio (SNR), Interference Level, Channel Quality Metrics, Modulation Coding Schemes (MCS), Primary User Activity Metrics and User Density. The main goal of integrating MLP on data attribute of HPSTSO approach is to utilize the MLP model to predict resource demands for optimal allocations based on generated historical data, which can then improve the HPSTSO algorithm's decision-making process.
(f) RadioML2016.10B dataset is used to evaluate the proposed system.

Furthermore, the key components of the proposed network include Secondary Users (SUs), a FC, Primary Users (PUs), and Base Stations for Primary Users (BS-PUs).

A. Secondary Users (SUs): The SUs are the nodes responsible for transmitting and receiving data in the cognitive network. They are equipped with cognitive radio capabilities, allowing them to dynamically access and utilize available spectrum channels. The SUs performs spectrum sensing, maintain routing tables, and select optimal paths for data transmission based on the information provided by the FC.
B. The FC: It acts as the central entity that manages the overall spectrum and channel allocation decisions. It collects entire spectrum sensing data from the SUs, maintains a spectrum availability database, and performs dynamic spectrum allocation. The FC also calculates optimal routing paths and shares this information with the SUs to guide their routing decisions.
C. Primary Users (PUs): They are the licensed users of the spectrum, and their communication has priority over the SUs. The SUs must ensure that their transmissions do not interfere with the PUs' communication.
D. The Base Stations for Primary Users (BS-PUs): It serves as the access points for the PUs, providing them with connectivity to the network infrastructure.

The proposed cognitive network supports wireless communication and mobility, allowing SUs to move freely within the network. Different mobility types, such as linear and random mobility, are supported. The dynamic spectrum access feature enables the SUs to adapt to changing spectrum availability and network conditions, ensuring efficient and reliable data transmission. In the proposed architecture, each component plays a crucial role in ensuring reliable communication and efficient resource management in cognitive radio networks. These components create a robust framework for HPSTSO applications, as it shown in Figure 3.

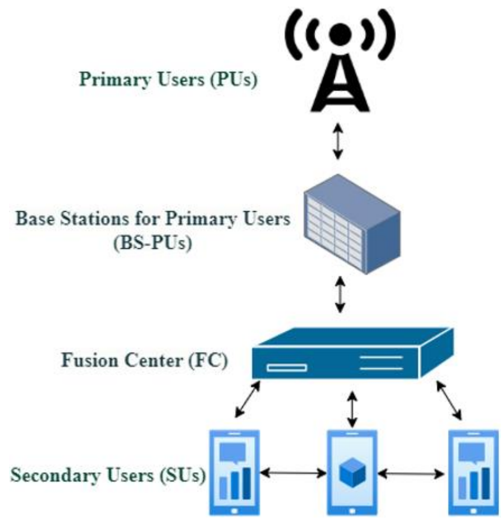

Figure 3. The proposed network topology

During the modeling and validation phase of the predictive model, there is a set of settings and assumptions that show that the basic data follows a normal distribution in building statistical methods. These assumptions were applied to all study cases, whether for the hybrid HPSTSO resource management system or the machine learning system for a MLP algorithm and for all datasets used, whether the dataset that was own created CAMOD dataset from the first stage of resource allocation, as well as the standard dataset that was used and compared with the proposed MLP system.

Besides, simulation parameters of the proposed system sorted in Table 2.

The proposed system implemented in OMNET ++. The network topology which consists of 10 Primary Users as available channels, 20 Secondary Users, as Cognitive radio nodes which send and receive data types (Text, Image and Files). Figure 4 showed the node connectivity of the proposed HPSTSO system case study.

Figure 5 showed message passing among FC and SU to share their positions parameters, data signal, route information and velocities to optimize resource allocation effectively in the proposed cognitive radio network.

Figure 6 showed channel optimization between BS-PUs and PUs and acknowledged channel idle by BS-PUs to the FC which is used as free channel for spectrum allocation of SUs nodes.

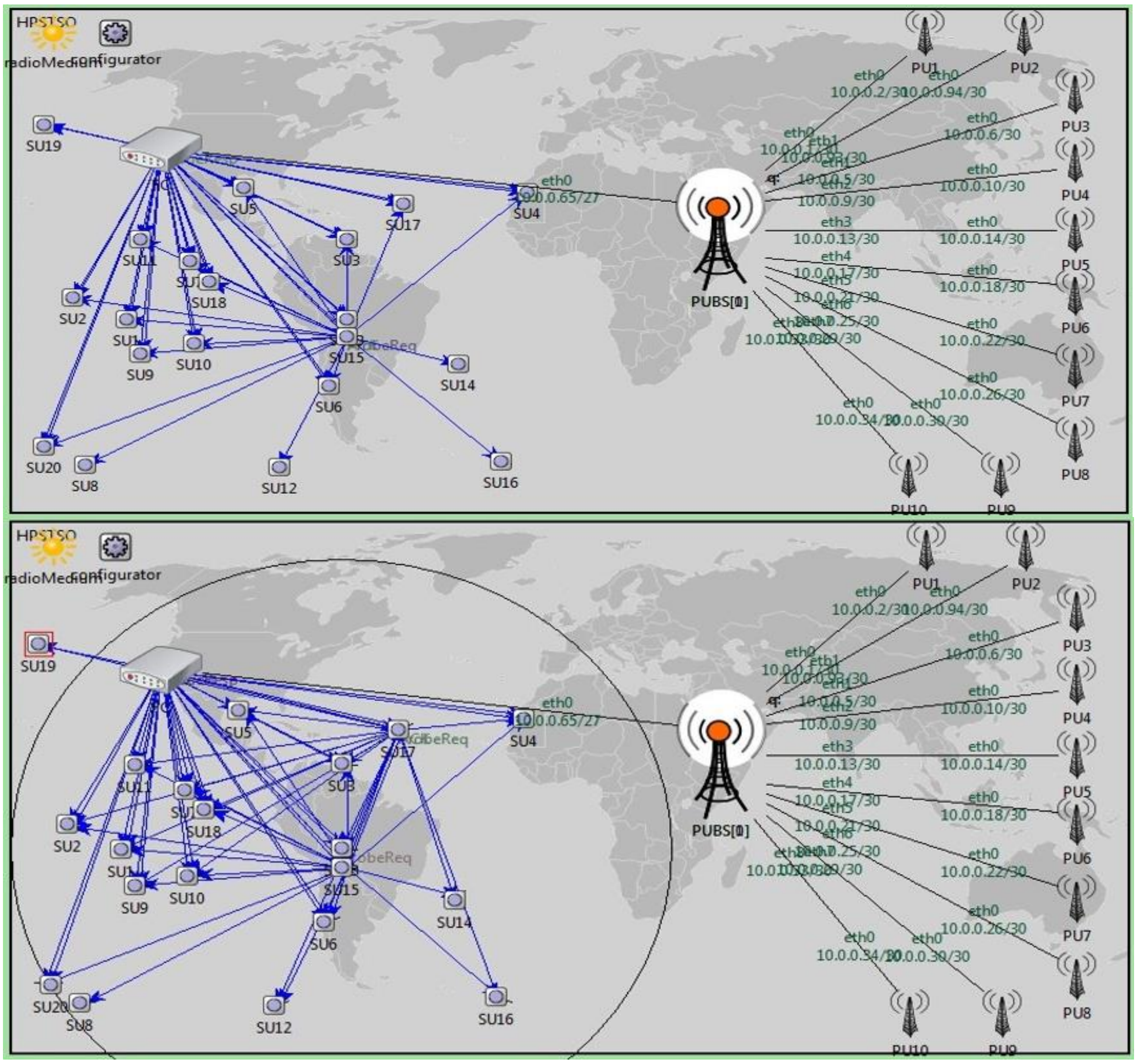

Figure 4. Node connectivity of the proposed HPSTSO approach

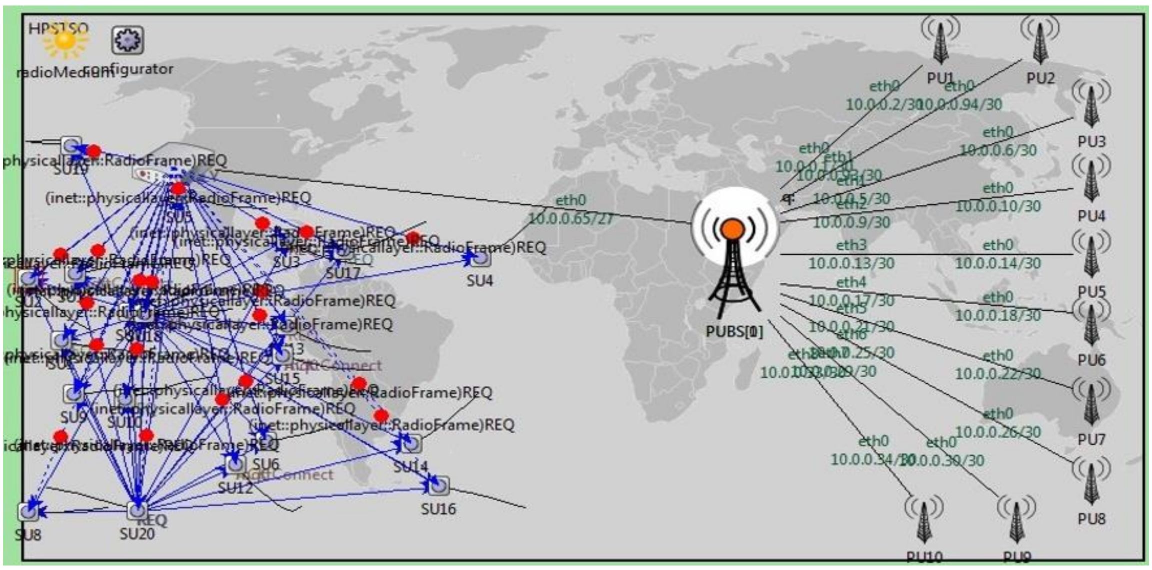

Figure 5. Message-passing of HPSTSO among FC and SUs

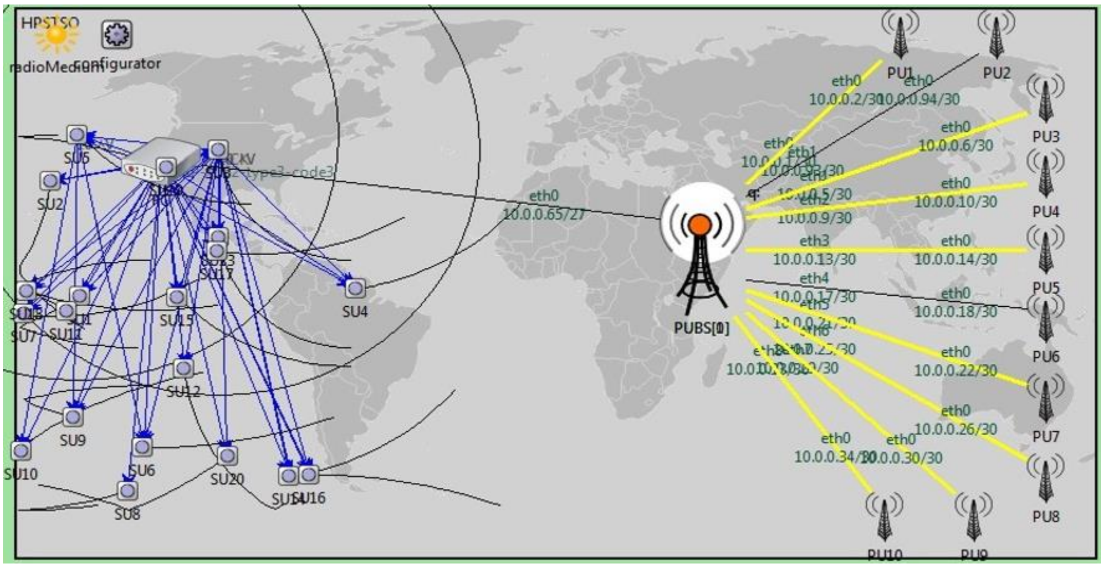

Figure 6. PU channel optimization by HPSTSO approach

Table 2. Simulation parameters and considered values of the proposed system

Simulation Parameters		Considered Value
Network area		500 m × 500 m
Mobility of SU nodes		Dynamic
Mobility speed of SU node		5 ms
Nodes distance		Random
Bandwidth size for each channel		5 MB/s
Number of PU		10
Number of SU nodes		20
Transmission range of PU		300 meters
FCs and Sus		500 meters
Total no. of FCs		1
Channel availability probability		0.95
Data Type	Text data signal size	100 B
	Image data signal size	80 KB
	Audio data signal size	580 KB
	Video data signal size	950 KB
Simulation time		1800 seconds
Type of channel		Wireless
Simulator name		OMNET ++ 6.0
RAM size		8 GB
CPU		Core i 7

5. RESULTS

The proposed system relied on a variety of data traffic that simulates the application of cognitive radio in healthcare in terms of the nature of data traffic in the network. The proposed system addressed a set of scenarios for different types of data such as text data, image data, and audio, videos and files, with different data sizes passing through radio channels and transmitted between SU nodes in the network. The results summarized the importance of resource management in the network in order to ensure the best scenario for data traffic and ensure the quality of communication for secondary users in cognitive radio networks.

The proposed system results are explained as follows:

5.1 Network evaluation results

The results of the proposed system depend on the performance improvement of the proposed hybrid algorithm, as it showed significant improvements in many performance measures compared to other algorithms, as the packet delivery rate improved as a result of the ease of transferring data more efficiently and maintaining reliable communication between secondary users in the cognitive radio network, as the packet delay was reduced from the beginning of its creation to the second party that receives this packet, which shows the algorithm's ability to accelerate data processing and transmission time and thus make a faster decision in a dynamic environment compared to other methods followed by the two proposed algorithms. The proposed results are based on four case studies: without resource optimization, optimization using the PSO algorithm, optimization using the TS algorithm, and resource optimization using the hybrid HPSTSO algorithm.

A. Results without optimization

In the absence of resource optimization techniques, the results and evaluation of the system showed poorer performance compared to systems using algorithms, as traditional methods struggle to route data through available channels, causing inefficiency for secondary users in the cognitive radio network due to increased packet delay and communication delays, putting it in real-time monitoring capabilities, as well as less effective decision-making processes and poor signal quality due to increased susceptibility to interference, which causes a higher probability of channel collision due to insufficient management of channel access, and thus a decrease in the overall efficiency of spectrum utilization, which causes drawbacks when using this strategy to manage resources in the network.

B. Results of PSO

The results showed resource optimization improvement compared to the system of without resource optimization or the TS algorithm, the noticeable increase in the evaluation metrics as a result of improving the data transmission path, reducing packet loss, and reducing the delay of its arrival time, as well as improving decision-making processes after reducing the waiting time to reach the channel, as well as reducing the processing time in general, as this algorithm has proven its ability to choose the channel with the best quality and the least interference to maintain a strong, stable connection and reduce the possibility of collisions between channels, which clarified the effectiveness of this algorithm in improving the performance of systems based on the health aspect in cognitive radio networks compared to both cases without improvement and the case of the TS algorithm.

C. Results of TS optimization

The results of this algorithm showed an improvement compared to the case without resource allocation and to a lesser degree than the PSO algorithm, as it proved its ability to transfer data, reduce packet delay, enhance data routing efficiency and deliver it faster. It also showed its ability to find solutions to simplify decision-making processes and increase the signal-to-noise ratio, which results in choosing channels with better signal quality and less interference, in addition to maximizing productivity and improving system performance, especially in scenarios that require strong and reliable communications between different network components.

D. Results of HPSTSO

The results area of the hybrid system is an advantage compared to the previous study cases of the PSO and TS algorithm in evaluating the network performance, as it has proven significant improvements in increasing the packet delivery ratio, which reflects the effectiveness and externality of the hybrid in improving data transmission paths and reducing packet loss with a decrease in the latency of arrival. It also showed the ease of making decisions to choose the empty channel and the decrease in the probability of secondary users colliding to obtain the channel, as this algorithm combines the strengths of both the PSO algorithm and the TS algorithm to enhance decision-making processes and simplify computational processes in improving productivity while ensuring effective spectrum use and increasing reliability and efficiency in improving resource utilization for the cognitive radio network.

Figure 7 showed that the hybrid system significantly outperforms the other methods in terms of throughput, achieving 21,379 Mb/s, which is significantly higher than both PSO and TS algorithms, as well as the case without optimization, in which the throughput dropped to only 8624 Mb/s. This performance is attributed to the strength of the hybrid approach, which effectively outperforms all the PSO and TS algorithms, and its more efficient use of resources, which contributed to enhancing the data processing capabilities of the network.

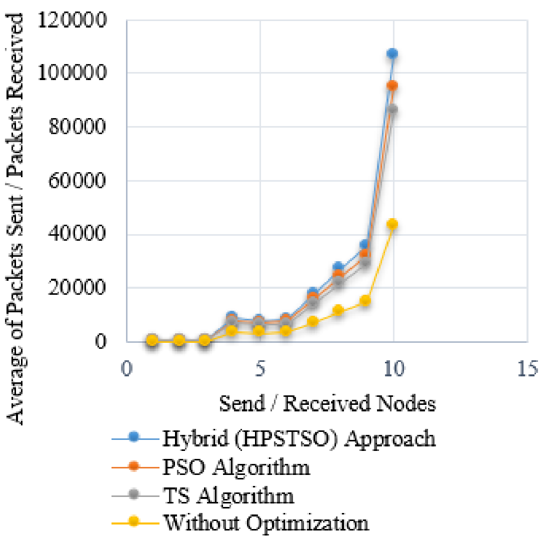

Figure 7. The average of throughput in Mbps for packets sent and packets received

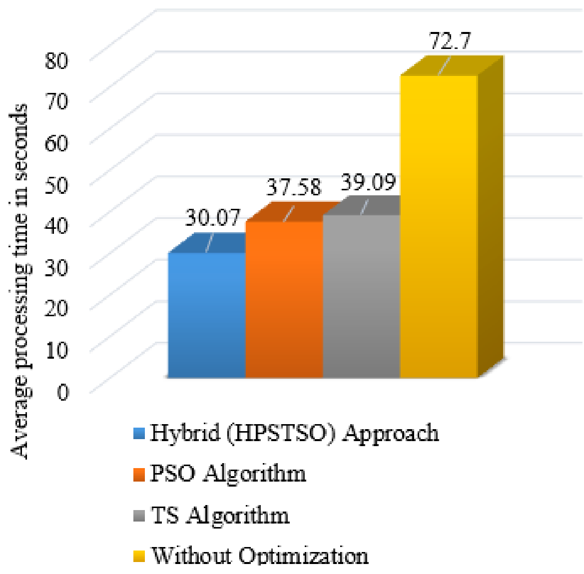

Figure 8. The average processing time in seconds of the used algorithms

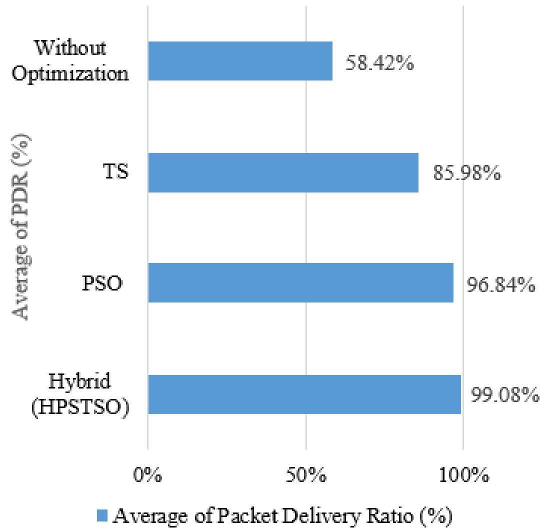

Figure 9. The average of packet delivery ratio of the proposed hybrid approach

Figure 8 showed the hybrid HPSTSO is an efficient approach characterized by an average processing time of 30 seconds, which makes it the fastest option compared to the PSO and TS algorithms. This proposed system not only achieves higher productivity, but also significantly reduces the processing time, which enhances the overall performance of the system and the speed of response.

Figure 9 showed the percentage of average packet delivery ratio demonstrates the effectiveness of the hybrid HPSTSO approach compared to other methods, achieving a delivery ratio of 99%, indicating that almost all packets were successfully delivered. These results confirm the HPSTSO system ability to maintain high packet delivery rates, which is critical in ensuring reliable communication and data integrity in a cognitive radio network.

Figure 10 showed the average packet delay for the different algorithms in the proposed system, where the hybrid HPSTSO approach proved an average delay of 30,929 milliseconds as the lowest average delay for packet transmission in the network. The results indicate the efficiency of the hybrid HPSTSO system in reducing packet delay, which is reflected in the efficiency of the network in general compared to other methods.

Figure 11 showed the efficiency of the hybrid HPSTSO system compared to the PSO algorithm and the TS algorithm in finding the congestion-free channel rate of 99.17%, which indicates reducing channel congestion and reducing unjustified channel occupation, which reduces network performance and affects the smooth transmission of data.

Figure 12 showed average probability of channel collision in the network where the HPSTSO method achieved a low collision probability of 0.0508 which indicates the use of a high efficiency which enhances the overall performance of the network and makes it a superior choice for improving channel utilization in cognitive radio networks.

Figure 13 showed that the hybrid HPSTSO system is effective in maximizing network capacity and resource efficiencies compared to other algorithms, highlighting the efficiency of the proposed hybrid system in improving the overall system performance and network resources.

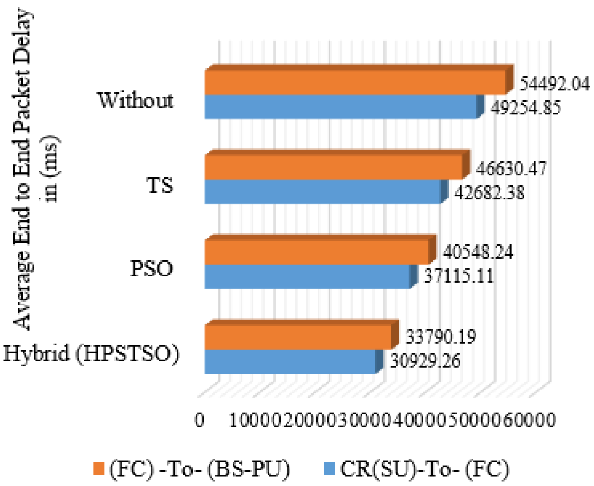

Figure 10. The average end-to-end packet delay of the proposed HPSTSO approach

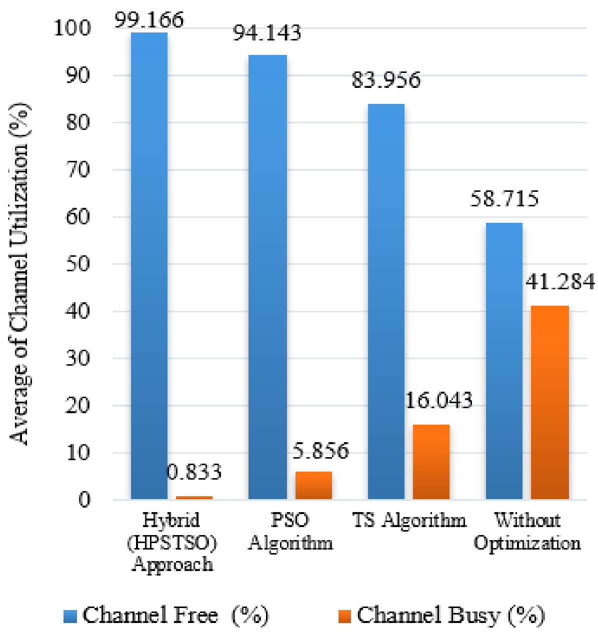

Figure 11. The average of channel utilization of the proposed HPSTSO approach

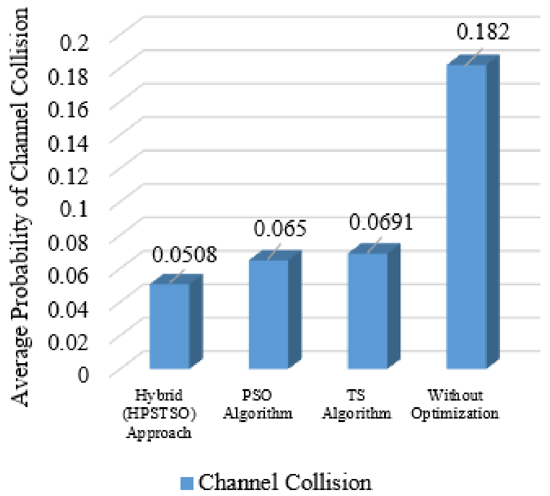

Figure 12. The average probability of channel collision of the proposed HPSTSO approach

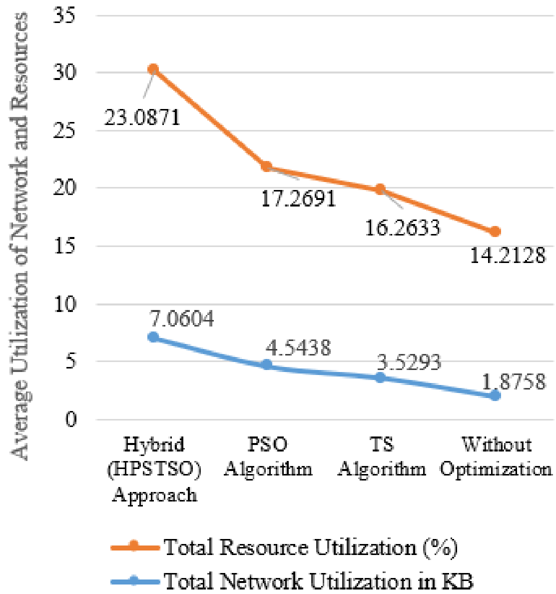

Figure 13. The average of network and resource utilization of the proposed HPSTSO approach

Figure 14 showed the differences in performance for the signal-to-noise ratio results. The hybrid HPSTSO approach achieved a ratio of 7.33 dB, which indicates its effectiveness in maintaining a strong signal in a light environment. This is much higher than the proposed PSO and TS algorithms. The hybrid approach shows its superior ability to improve signal strength, making it the most reliable choice for effective communication in noisy environments.

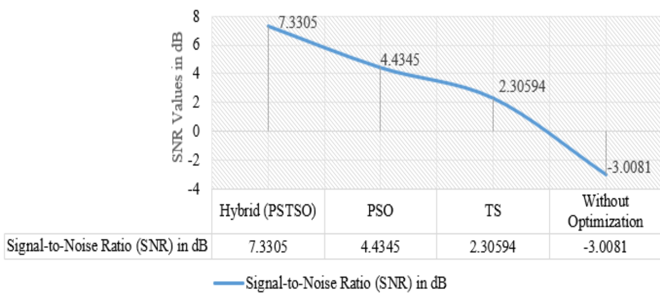

Figure 14. The average of SNR of the proposed HPSTSO approach

Table 3. Average PDR of the proposed system compared with other related works

References	No. of SU, PU Nodes	Environment	Method	Average PDR%
[23]	100,10	MATLAB	Hybrid Firefly and Grey-Wolf Optimization-Based Spectrum Map-Empowered Opportunistic Routing (HFGWOSMOR)	97.5%
[24]	10 to 50,10 to 50	Network Simulator	Optimizing Multichannel Path Scheduling (OMPS)	97%
			Path Discovery for End-to-End Data Transmission (PDDT)	93.5%
The proposed hybrid optimization approach	20, 10	OMNET ++	HPSTSO	99.08%
			PSO algorithm	96.84%
			TS algorithm	85.98%

Table 3 showed the proposed Hybrid Particle Swarm-Tabu Search Optimization (HPSTSO) approach compared with other related works associated with the routing approach in cognitive radio network. There is a gap in the relevant work related to the shortage of spectrum resources and low utilization rate without impact on licensed users in cognitive radio networks. The high average results, especially the packet delivery results, indicate that the proposed spectrum management approach is effective in ensuring reliable communication between nodes in a cognitive radio network. The implications for future spectrum management are improved spectrum efficiency due to the effectiveness of the proposed approach in managing the active spectrum while reducing interference between primary and secondary users, as well as supporting dynamic spectrum access, which allows real-time adjustments based on network conditions and data user requirements.

5.2 Results of machine learning algorithm

The proposed system results are based on two datasets (CAMOD and RadioML2016.10B) mainly each dataset is split into (70% training and 30% testing. The preprocessing model used is the same for both datasets. The first created dataset CAMOD contains the total number of columns and rows explained in Table 4.

Table 4. Number of records and attributes of CAMOD dataset

CAMOD Dataset Features	
Number of records	207993
Number of attributes	15

A. Results of hybrid optimization HPSTSO without preprocessing of CAMOD dataset

Table 5. The results without preprocessing of the MLP algorithm on the CAMOD dataset

Method Name	Accuracy	Confusion Matrix		Time
		False Positive Rate	False Negative Rate	
MLP	94.144%	0.9075	5.6499	132728 ms

The results show that applying the hybrid optimization algorithm without preprocessing on the CAMOD dataset, a single performance of 94.14% is considered a high level of predictive accuracy, as well as a false positive rate of 0.9075, which requires room for improvement in reducing false positives based on the total processing time of 132728 ms, which reflects the computational requirements for training and evaluating the complex neural network in general and needs further improvement. Table 5 shows the accuracy and time results of the used dataset.

The results in Table 6 showed the algorithm's ability to handle classification effectively and its ability to achieve accuracy even in the absence of database refinement.

Table 7 showed a set of evaluation parameters for the proposed algorithm on the CAMOD dataset. The results showed that the model predicted the positive class with an accuracy of 0.91791, a detection rate of 0.1503, and a false alarm rate of 90%. These highs indicate a large number of negative cases that were incorrectly classified as positive, as well as a set of other parameters that indicate the presence of discrepancies between the predicted and actual values, a low detection rate, and a high false alarm rate, which require further improvement of the overall performance of the model.

Table 6. Correctly and incorrectly classified the MLP algorithm on the CAMOD dataset

Machine Learning Algorithm	Correctly Classified	Incorrectly Classified
MLP Neural	195812 = 94.1440%	12180 = 5.8559%

Table 7. Evaluation of MLP algorithm based on the CAMOD dataset

Evaluation Parameters	Machine Learning Algorithms
	MLP
Precision	0.91791
Detection Rate (DR)	0.1503
False Alert Rate (FAR)	0.9075
Area Under Curve (AUC)	0.2166
True Positive (TP) Rate	0.9994
True Negative (TN) Rate	0.0924
Mean Absolute Error	0.04857
Relative Absolute Error (RAE)	74.1629
Root Relative Squared Error (RRSE)	95.2216
Error Rate	0.05855

Table 8 showed the performance of the proposed MLP algorithm on the CAMOD dataset. The low Recall value indicates that the model is able to identify 9% of the actual positive cases, which highlights the major challenge in capturing cases. Also, the F-value between precision and recall is relatively low, so the model struggles for overall effectiveness in case classification. As for the Kappa coefficient, which measures the agreement between predicted and actual classifications, it is also low, which requires better model performance.

Table 8. Recall, the F-Measure and Kappa coefficient of the without preprocessing of MLP algorithm based on the CAMOD dataset

Machine Learning Algorithm	Recall	F-Measure	Kappa Coefficient
Multilayer Perceptron (MLP) Neural	0.0924	0.1680	0.1581

B. Results of hybrid optimization HPSTSO with preprocessing of CAMOD dataset

This case depends on refining the CAMOD database that was created in the first part of the system using resource optimization techniques and managing the data transfer process in the network, as the proposed algorithm is based on the MLP machine learning model, which achieved detection accuracy in sectarian sensing, whether sensing the radio spectrum, whether from secondary users or primary users, as Table 9 showed a percentage of 99.45%, a high level of performance according to a low false positive rate of 0.0085, which indicates the effectiveness of the proposed refinement system in correctly identifying categories and high prediction capabilities according to a very short processing time that contributes to investing time to move between the channels proposed by FC.

Table 9. The accuracy of hybrid optimization HPSTSO with preprocessing of CAMOD dataset

Method Name	Accuracy	Confusion Matrix		Time
		False Positive Rate	False Negative Rate	
MLP Neural	99.4503%	0.00855	0.0	109902 ms

Table 10 showed the exceptional performance in classifying data from the proposed database and the low error rate as a result of the reliability of the model and its strength in making predictions related to radio spectrum sensing. It is considered suitable for applications that require very accurate classification results and high-level performance applicable in realistic scenarios.

Table 10. Correctly and incorrectly classified of HPSTSO with preprocessing of CAMOD dataset

Machine Learning Algorithm	Correctly Classified	Incorrectly Classified
MLP Neural	206850 = 99.4503%	1143 = 0.5496%

The results in Table 11 and Table 12 showed that all the positive predictions made by the model were correct, which indicates complete accuracy that contributed to a detection rate that correctly identifies all actual positive cases, as well as a low false alert rate, as the model generates very few false positives, and thus false alerts are few and do not cost the system any acquisition operations. The model's ability to distinguish between categories was high, as it succeeded in identifying all positive cases as well as identifying negative cases.

The results indicate a significant improvement in resource allocation efficiency when employing the hybrid PSTSO optimization compared to traditional methods. Specifically, the hybrid approach demonstrated a marked increase in throughput and resource utilization while effectively reducing interference among SUs. The evaluation metrics revealed that the hybrid optimization outperformed both the PSO and TS methods individually, showcasing the benefits of combining these two powerful algorithms. Furthermore, the preprocessing of data prior to applying the MLP model yielded superior results in terms of accuracy and F-measure, indicating that data quality plays a crucial role in enhancing machine learning outcomes. Overall, the results highlight the effectiveness of the HPSTSO model in optimizing spectrum allocation within CRNs, providing a robust framework for future research and practical applications in cognitive radio systems.

Table 11. Evaluation of HPSTSO with preprocessing of CAMOD dataset

Evaluation Parameters	Machine Learning Algorithms
	MLP
Precision	1.0
Detection Rate (DR)	1
False Alert Rate (FAR)	0.00855
Area Under Curve (AUC)	0.99789
True Positive (TP) Rate	1.0
True Negative (TN) Rate	0.9914
Mean Absolute Error	0.00626
Relative Absolute Error (RAE)	1.75699
Root Relative Squared Error (RRSE)	12.1041
Error Rate	0.0054

Table 12. Recall, F-Measure and Kappa coefficient of HPSTSO with preprocessing of CAMOD dataset

Machine Learning Algorithm	Recall	F-Measure	Kappa Coefficient
MLP Neural	0.9838	0.9918	0.9922

C. Results of the preprocessing approach of RadioML2016.10B dataset

The proposed algorithm is tested with the RadioML2016.10B dataset with a total sample sum of 240,000. The entire sample sets, which include both signal and noise, have been labelled for training, validation, and classification. The RadioML2016.10b dataset includes several specific attributes that characterize the radio signals it contains. The main attributes are as follows:11 Modulation Type, SNR, Sample Frame Size, Number of Samples, and Channel Effects. Table 13 showed number of records and attributes of RadioML2016.10B dataset.

Table 13. Number of records and attributes of RadioML2016.10B dataset

RadioML2016.10B Dataset Features	
Number of records	240000
Number of attributes	15

In cognitive radio networks, spectrum sensing is crucial for identifying unused frequency bands that can be utilized by secondary users without interfering with primary users. Table 14 showed the resulting accuracy of 98.7% in this context means that the MLP can reliably detect these opportunities, leading to better resource utilization and reduced interference.

Table 14. Accuracy, confusion matrix and time of the RadioML2016.10B dataset after the preprocessing approach

Method Name	Accuracy	Confusion Matrix		Time
		False Positive Rate	False Negative Rate	
MLP Neural	98.7	0.02281	1.28406	121494 ms

Table 15. Correctly and incorrectly classified the RadioML2016.10B dataset after the preprocessing approach

Machine Learning Algorithm	Correctly Classified	Incorrectly Classified
MLP Neural	236880 = 98.7%	3120 = 1.3%

Table 16. Evaluation of the RadioML2016.10B dataset after the preprocessing approach

Evaluation Parameters	Machine Learning Algorithms
	MLP
Precision	0.9998
Detection Rate (DR)	0.4377
False Alert Rate (FAR)	0.0228
Area Under Curve (AUC)	0.9919
True Positive (TP) Rate	0.9998
True Negative (TN) Rate	0.9771
Mean Absolute Error	0.01191
Relative Absolute Error (RAE)	3.4233
Root Relative Squared Error (RRSE)	18.7016
Error Rate	0.013

Table 17. Recall, the F-Measure and Kappa coefficient of the RadioML2016.10B dataset after the preprocessing approach

Machine Learning Algorithm	Recall	F-Measure	Kappa Coefficient
MLP Neural	0.9576	0.9782	0.9809

Tables 15-17 show the extent of improvement shown by the proposed system based on correctly classified cases at a rate of 98.7% of the total data set. This is a result of the effectiveness of the preprocessing method in increasing the efficient network performance on the database, as it led to increasing the accuracy of the model in classifying and identifying signal modifications within the RadioML2016.10B database and reducing the low error rate. In addition, the vast majority of positive predictions provided by the model are correct, which indicates an exceptional level of accuracy and the detection rate of actual positive cases is normal, as well as the low percentage of false alert rates and the ability of the proposed system to distinguish between categories based on the proposed algorithm contributed to the increase in the true positive rate with a decrease in the average absolute error, which contributed to improving the algorithm's ability to find efficient practical detection in classifying wireless signals for the RadioML2016.10B database.

6. SYSTEM COMPARISON

The results are compared with other works as well as the comparison with the system for both cases before and after data preprocessing, where the comparison showed an increase in the accuracy of the sensitivity detection of the radio frequency spectrum and the extent of the improvement that occurred in a group of evaluation parameters, as in Table 18. In addition, the practical implications of the proposed system results inspired from the real-world scenarios and the model expansion to adapt to different environmental conditions showed that the system adapts to heavy wireless traffic, making it suitable for implementation in different contexts from urban areas to rural environments, depending on the nature of data traffic in the network, with high density and very fast data transfer capacity, taking into account different channel conditions, whether with or without noise and collision in the network, and providing actionable insights for real-world applications for spectrum management, as well as addressing the increasing demands on wireless communications while ensuring efficient performance across different environments.

Table 18. The proposed HPSTSO system comparison

References	Dataset	Algorithm	Accuracy	Precision	Recall	F1 Score
[25]	RadioML2016.10A	PU-DetNet	97.55%	0.925	0.872	0.898
[26]	RadioML2016.10B	RBRLG	95.7%	0.957	0.860	0.906
[27]	RadioML2016.10B	CNN-TN	97%	0.957	0.895	0.925
The proposed system	**RadioML2016.10B**	**MLP**	**98.7**	**0.9998**	**0.9576**	**0.9782**
	Own created (CAMOD dataset)		**99.45%**	**1.0**	**0.9838**	**0.9918**

7. CONCLUSIONS

The broader implications of applying the proposed CAMOA based HPSTSO system contributed to improving problem solving to face the challenges of limited energy systems and logistics communications by achieving an effective balance between exploring operations and exploiting resources to implement hybrid method by moving across execution operation spaces more efficiently than traditional methods of the single method resource optimization system as well as the ability to adapt and be flexible for the HPSTSO system with changing and symmetrical environments in problems, which advances to adapting the system to different applications requirements without reconfiguring the system intensively by integrating time-reducing strategies with improving the quality of the solution, as traditional optimization techniques are affected due to these techniques exhausting requirements for resources. The future research directions of the proposed system are real-time spectrum allocation based on dynamic network conditions of user requirements, building secure framework that protect against jamming and eavesdropping of cognitive radio networks vulnerabilities.

REFERENCES

[1] Alam, M.M., Malik, H., Khan, M.I., Pardy, T., Kuusik, A., Le Moullec, Y. (2018). A survey on the roles of communication technologies in IoT-based personalized healthcare applications. IEEE Access, 6: 36611-36631. https://doi.org/10.1109/ACCESS.2018.2853148

[2] Aceto, G., Persico, V., Pescapé, A. (2018). The role of information and communication technologies in healthcare: Taxonomies, perspectives, and challenges. Journal of Network and Computer Applications, 107: 125-154. https://doi.org/10.1016/j.jnca.2018.02.008 https://doi.org/10.1016/j.jnca.2018.02.008

[3] Vidakis, K., Mavrogiorgou, A., Kiourtis, A., Kyriazis, D. (2020). A comparative study of short-range wireless communication technologies for health information exchange. In 2020 International Conference on Electrical, Communication, and Computer Engineering (ICECCE), Istanbul, Turkey, pp. 1-6. https://doi.org/10.1109/ICECCE49384.2020.9179478

[4] Kartsakli, E., Lalos, A.S., Antonopoulos, A., Tennina, S., Di Renzo, M., Alonso, L., Verikoukis, C. (2014). A survey on M2M systems for mHealth: A wireless communications perspective. Sensors, 14(10): 18009-18052. https://doi.org/10.3390/s141018009

[5] Hamood, A.S., Sadkhan, S.B. (2017). Cognitive radio network security status and challenges. In 2017 Annual Conference on New Trends in Information & Communications Technology Applications (NTICT), Baghdad, Iraq, pp. 1-6. https://doi.org/10.1109/NTICT.2017.7976105

[6] Aslam, M.M., Du, L., Zhang, X., Chen, Y., Ahmed, Z., Qureshi, B. (2021). Sixth generation (6G) cognitive radio network (CRN) application, requirements, security issues, and key challenges. Wireless Communications and Mobile Computing, 2021(1): 1331428. https://doi.org/10.1155/2021/1331428

[7] Ding, H.C., Fang, Y.G., Huang, X.X., Pan, M., Li, P., Glisic, S. (2017). Cognitive capacity harvesting networks: Architectural evolution toward future cognitive radio networks. IEEE Communications Surveys & Tutorials, 19(3): 1902-1923. https://doi.org/10.1109/COMST.2017.2677082

[8] Hamood, A.S., Sadkhan, S.B. (2017). Keywords sensitivity recognition of military applications in secure CRNs environments. In 2017 Second Al-Sadiq International Conference on Multidisciplinary in IT and Communication Science and Applications (AIC-MITCSA), Baghdad, Iraq, pp. 96-101. https://doi.org/10.1109/AIC-MITCSA.2017.8722991

[9] Le, T.T.T., Moh, S. (2019). A spectrum-aware priority-based link scheduling algorithm for cognitive radio body area networks. Sensors, 19(7): 1640. https://doi.org/10.3390/s19071640

[10] Ahmadi, H., Arji, G., Shahmoradi, L., Safdari, R., Nilashi, M., Alizadeh, M. (2019). The application of internet of things in healthcare: A systematic literature review and classification. Universal Access in the Information Society, 18: 837-869. https://doi.org/10.1007/s10209-018-0618-4

[11] Castaneda, E., Silva, A., Gameiro, A., Kountouris, M. (2016). An overview on resource allocation techniques for multi-user MIMO systems. IEEE Communications Surveys & Tutorials, 19(1): 239-284. https://doi.org/10.1109/COMST.2016.2618870

[12] Kamal, M.A., Raza, H.W., Alam, M.M., Su'ud, M.M., Sajak, A.B.A.B. (2021). Resource allocation schemes for 5G network: A systematic review. Sensors, 21(19): 6588. https://doi.org/10.3390/s21196588

[13] Siddiqi, M.H., Alruwaili, M., Ali, A., Haider, S.F., Ali, F., Iqbal, M. (2020). Dynamic priority-based efficient resource allocation and computing framework for vehicular multimedia cloud computing. IEEE Access, 8: 81080-81089. https://doi.org/10.1109/ACCESS.2020.2990915

[14] Tsiropoulos, G.I., Dobre, O.A., Ahmed, M.H., Baddour, K.E. (2014). Radio resource allocation techniques for efficient spectrum access in cognitive radio networks. IEEE Communications Surveys & Tutorials, 18(1): 824-847. https://doi.org/10.1109/COMST.2014.2362796

[15] Freitas, D., Lopes, L.G., Morgado-Dias, F. (2020). Particle swarm optimisation: A historical review up to the current developments. Entropy, 22(3): 362. https://doi.org/10.3390/e22030362

[16] Kaur, A., Kumar, K. (2022). A comprehensive survey on machine learning approaches for dynamic spectrum access in cognitive radio networks. Journal of Experimental & Theoretical Artificial Intelligence, 34(1): 1-40. https://doi.org/10.1080/0952813X.2020.1818291

[17] Abbas, N., Nasser, Y., Ahmad, K.E. (2015). Recent advances on artificial intelligence and learning techniques in cognitive radio networks. EURASIP Journal on Wireless Communications and Networking, 2015: 1-20. https://doi.org/10.1186/s13638-015-0381-7

[18] Bakshi, S., Sharma, S., Khanna, R. (2022). A novel metaheuristic optimization for throughput maximization in energy harvesting cognitive radio network. Elektronika ir Elektrotechnika, 28(3): 78-89. https://doi.org/10.5755/j02.eie.31245

[19] Srivastava, V., Singh, P., Malik, P.K., Singh, R., Tanwar, S., Alqahtani, F., Tolba, A., Marina, V., Raboaca, M.S. (2023). Innovative spectrum handoff process using a machine learning-based metaheuristic algorithm. Sensors, 23(4): 2011. https://doi.org/10.3390/s23042011

[20] Eappen, G., Shankar, T. (2020). Hybrid PSO-GSA for energy efficient spectrum sensing in cognitive radio network. Physical Communication, 40: 101091. https://doi.org/10.1016/j.phycom.2020.101091

[21] Latif, S., Akraam, S., Malik, A.J., Abbasi, A.A., Habib, M., Lim, S. (2021). Improved channel allocation scheme for cognitive radio networks. Intelligent Automation & Soft Computing, 27(1): 103-114. http://doi.org/10.32604/iasc.2021.014388

[22] Tavares, C.H.A., Marinello, J.C., Proenca Jr, M.L., Abrao, T. (2020). Machine learning—based models for spectrum sensing in cooperative radio networks. IET Communications, 14(18): 3102-3109. https://doi.org/10.1049/iet-com.2019.0941

[23] Abdullah, H.M.A., Kumar, A.S., Ahmed, A.A.Q., Mosleh, M.A.S. (2023). Hybrid optimization based on spectrum aware opportunistic routing for cognitive radio ad hoc networks. Информатика и автоматизация, 22(4): 880-905. https://doi.org/10.15622/ia.22.4.7

[24] Dasari, R., Venkatram, N. (2024). Optimizing multichannel path scheduling in cognitive radio Ad HoC networks using differential evolution. Scalable Computing: Practice and Experience, 25(2): 1199-1218.

https://doi.org/10.12694/scpe.v25i2.2649
[25] Soni, B., Patel, D.K., Shah, S.B., López-Benítez, M., Govindasamy, S. (2022). Pu-DetNet: Deep unfolding aided smart sensing framework for cognitive radio. IEEE Access, 10: 98737-98751. https://doi.org/10.1109/ACCESS.2022.3206814
[26] Vijay, E.V., Aparna, K. (2023). RNN-BIRNN-LSTM based spectrum sensing for proficient data transmission in cognitive radio. e-Prime-Advances in Electrical Engineering, Electronics and Energy, 6: 100378. https://doi.org/10.1016/j.prime.2023.100378
[27] Vijay, E.V., Aparna, K. (2024). Deep learning-CT based spectrum sensing for cognitive radio for proficient data transmission in wireless sensor networks. e-Prime-Advances in Electrical Engineering, Electronics and Energy, 9: 100659. https://doi.org/10.1016/j.prime.2024.100659