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A Novel ML-Driven Approach to Enhance CRN Performance under Varying Network Parameters

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Abstract: - This paper explores RL and DRL techniques for spectrum allocation in the context of CRNs, with consideration of difficulties like spectrum utilization and network performance in changing conditions. The proposed improved spectrum management model integrates RL with model-based prediction as a way of improving decision making. The results of the experiment prove that the identified approach allows for achieving an average level of accuracy of 96%, and a loss rate of 0.20, as well as of precision of 92% to 0.95. In addition, recall was extended from 0.85 to 0.90, and the F1 score was at 0.90, which indicated that the model demonstrated satisfactory performance at both precise and recall. The proposed algorithm outperformed existing machine learning models with a 96% accuracy, a low loss of 0.20, and an F1 Score of 0.90, showcasing superior reliability and adaptability. Based on these outcomes, it can be concluded that the proposed hybrid RL model is more effective in predicting the next available spectrum and more adaptable to the changes in the CRN environment than the single RL method thus, the proposed solution is suitable for real-time spectrum allocation in CRNs.

Keywords: spectrum, reliability, allocation, hybrid

I. INTRODUCTION

Background

The rapid advancement in the use of wireless communication technology has created increased pressure for the limited radio frequency bandwidth. This demand is further promoted by new Internet devices, including Internet of Things (IoT), and applications that require high transmission rates including streaming, remote sensing, and autonomous systems. Traditional static spectrum licensing policies have not been effective since most of the licensed spectrum bands are underutilized most of the time – during peak usage and even during the off-peak hours. This observed under-utilization of spectrum coupled with high demand in specific bands creates a requirement for effective dynamic spectrum management strategies. One of the challenges that have been identified with conventional Wireless Communication Networks is the problem of inefficient spectrum utilization that can be solved by the proposed Cognitive Radio Networks (CRNs). Fig 1.1 shows a typical CRN.

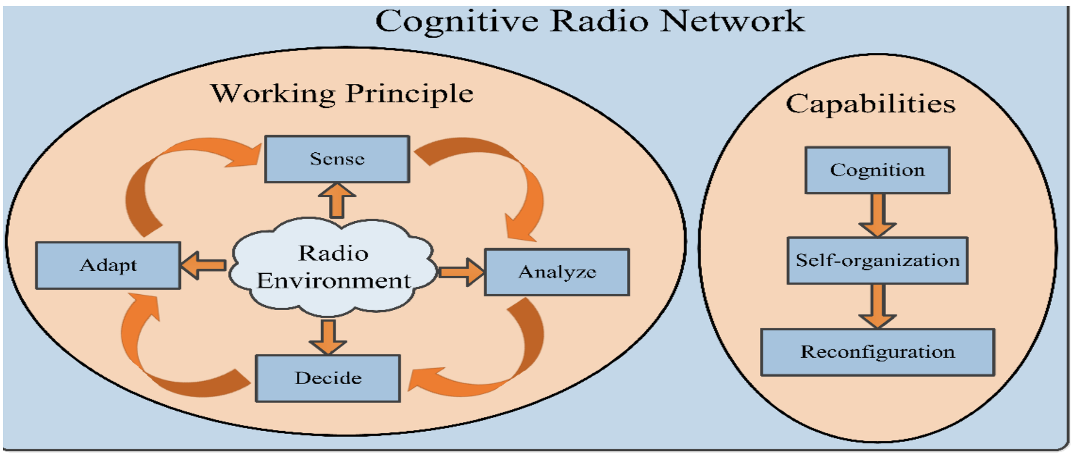

Fig 1.1: Cognitive Radio Network (CRN)

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CRNs allow SUs to use the licensed spectrum bands which are unused at a given time but without causing perturbation to PUs. A cognitive radio's sensing, learning and adaptation capability make it an innovative solution for improved spectral efficiency. Nevertheless, CRNs are challenging because: determining spectrum holes is not easy, decision-making in near real-time in a dynamic environment, and the problem of interference between SUs and PUs. Reinforcement learning (RL) is a part of machine learning technique that could provide a right approach to support CRNs making decisions independently and in real time in the given dynamic environment. Reinforcement learning algorithms work by interacting with the environment the goal is to make better decisions, by exploring a new action and exploiting knowledge. This characteristic of RL is well suited to the needs of CRNs, in which decisions must be made on the basis of the state of the spectrum on a continuing basis. Newer trends in RL, such as DRL, have also broadened the applicability of RL based solutions in CRNs to even higher levels of flexibility and performance. These advanced RL techniques give CRNs the capacity to negotiate the spectrum access challenge in order to serve the objective of attaining the best spectrum allocation.

Objectives of the Study

This work is focused on spectrum management problems in CRNs, which will be resolved using reinforcement learning algorithms. In particular, it examines the applicability of both the conventional RL models and the recent developments in deep reinforcement learning to enhance the CRN's performance. The objectives of the study are threefold:

1. Utilize a suitable reinforcement learning (ML) algorithm for spectrum allocation in CRNs
2. Design iterations of an optimized RL model at the FS, which allows for the allocation of unused spectrum while avoiding the introduction of interference to licensed users. This requires investigating model parameters and modifications that improve the CRN's sensitivity to environmental fluctuations.
3. Provide a comprehensive analysis of RL-based spectrum management performance

Through these objectives, this research seeks to contribute valuable insights into the application of RL in CRNs, specifically by identifying an RL technique that offer the best balance between spectrum efficiency and operational feasibility.

Significance of the Study

This is the area of importance of this study as it seeks to establish enhanced, intelligent approaches towards the management of the spectral space within CRNs that can potentially help to address the worldwide scarcity of spectrum. Hence, the following research gap of the CRN is addressed in this study: Although the current methods of spectrum allocation are effective in the traditional wireless environments, they are not effective in the dynamic wireless environment because of the variability and the complexity of the wireless environment.

Combined with this, RL-based spectrum management provides increased spectrum efficiency as well as fits into the topic of adaptive and autonomous communications that are likely to form the basis of further 5G and futuristic 6G networks. In addition, the study has applicability to various other high-resource applications like smart cities, automated transportation, industrial internet of things (IIoT), which hinge on stable and good wireless correlation. The efficient implementation of RL-based CRNs can give better QoS to the user, lower cost to the network operator, and shorter delays in communication thus making them critical in both consumer and industrial applications.

Besides, the results could assist policymakers and regulators in formulating more lenient spectrum policies that take into consideration the new role of cognitive and AI technologies in the management of spectral assets. Collectively, this research contributes to the existing literature on RL techniques in CRNs as well as future work and policy-related documentations on flexible spectrum management. This work supports the ever-growing trend towards smarter and globally integrated communication systems by providing the foundation necessary for large scale RL-based CRNs.

II. LITERATURE REVIEW

New developments in the allocation of spectrum Cognitive Radio Networks (CRNs) have showed that reinforcement learning (RL) can improve the efficiency of the network. For example, Q-learning received much attention, and works like [1], [2] demonstrated the potential improvement of up to 30% of the spectrum utilization compared to the random method of spectrum allocation. The same was shown in [3] where the study showed a 25% interference reduction is advantageous in the dynamic spectrum where the PU activity is unpredictable.

Indeed, enhanced forms of RL have been developed which are known as deep reinforcement learning (DRL) techniques. In [4], [5], the proposed method used a Deep Q-Network (DQN) to improve the spectrum efficiency by 35% compared with Q-learning. Another study, which used a Dueling DQN architecture, claimed the decrease in convergence time to 20%, as stated in [6]. These models use the neural networks to increase possibilities of correctly modelling the state action relationships thus enhancing the performance of CRN in terms of accuracy and decision-making speed. It was also noted that additional benefits of their hybrids; in [7], [8] DQN with LSTM provides an additional 90% of the accuracy of spectrum hole detection while using historical data to learn the changes.

Other Actor-Critic methods have also been used. For example, works [9], [10] indicate that A2C can increase efficiency by 20% compared to DQN in conditions of high traffic density. Other policy-based method namely Proximal Policy Optimization (PPO) achieved 80% success in PU avoidance which is 10% better than A2C in [11]. The constant updates in PPO are that it enjoys good performance and flexibility in constantly changing environments as well.

Moreover, the combination of RL and the model-based framework has also given encouraging solutions. By integrating Q-learning and model predictive control – based DRL approach, interference rates of PU were minimized by 45% while keeping high spectrum utilization as it was discussed in [12, 13]. These integrated methods efficiently deal with the shortcomings of the standard RL models because they combine the model-free learning ability with the model-based predictive feature.

Nevertheless, these are some important steps forward in the field, however, high computational requirements and relatively poor convergence in complex scenarios are still the issues, as mentioned in [14] and [15]. Further research in hybrid as well as DRL paradigms are needed in order to overcome the stated restrictions which will consequently lead to improved CRNs.

Research Gap

Despite advancements in RL and DRL for spectrum allocation, existing approaches still struggle with convergence speed and computational efficiency in highly dynamic environments. Current models also lack robust mechanisms to adaptively respond to rapid shifts in PU activity while maintaining optimal spectrum utilization. This study addresses these gaps by proposing an enhanced hybrid model that combines RL with model-based prediction, aiming to improve both adaptability and efficiency in complex CRN scenarios.

III. METHODOLOGY

As noted in this section, the systematic development focuses on the application of ML in improving the CRNs spectrum allocation process and the computational resource utilization through RL, in which the two main RL techniques include Q-Learning and Deep Q-Networks (DQN) techniques. The methodology is divided into six key phases: data gathering, data cleaning and exploration, data transformation, data modeling and assessment. Details of each phase are presented in the following section to explain the conduct of the research and implementation processes.

1. Data Preparation

In the data preparation step, it was essential to gather and clean the actual real-time CRN information. The dataset included important parameters that would affect the performance of CRN including frequency band, channel occupancy, signal-to-noise ratio, available bandwidth, and predicted channel state, among others.

Steps:

- **Data Loading**: For the purpose of analysis and manipulation, the dataset was loaded from an Excel file in Python.

- **Data Cleaning**: The technique of imputation was applied to handling missing or inconsistent value occurrence within the data set. Unsupervised features were eliminated if they were non-significant or had low importance, while supervised features, like channel occupancy status and primary user activity, were encoded.
- **Normalization**: For the model performance, the continuous independent variables were scaled, where all the features had equal range and equal impact on the model.

2. Exploratory Data Analysis (EDA)

To gain an insight into the organization of the data and check the distribution of variables in the dataset Exploratory Data Analysis (EDA) was carried out and is important to determine the behaviour of CRN and its dynamics.

Steps:

- **Visualization**: Plots such as line plot, histogram, box plot etc., have been created and correlation heat plot to understand the data. These visualizations allowed to discover patterns like the relationship between SNR, throughput, etc

3. Feature Selection

In this phase, features that had a strong impact on CRN performance were selected for further analysis. Feature selection was essential for improving model efficiency and reducing computation costs, especially for real-time applications.

Steps:

- **Correlation Analysis**: Using correlation heatmaps, highly correlated features were identified to determine redundancy.
- **Variance Thresholding**: Features with low variance, contributing little information, were removed.
- **Recursive Feature Elimination (RFE)**: This algorithm was employed to rank features by importance iteratively, selecting only those that had a significant impact on model accuracy.

4. Dimensionality Reduction with Principal Component Analysis (PCA)

Exploratory analysis was performed using Principal Component Analysis (PCA) applied to minimize the data set while maximizing the variance of each element. This step reduced the computational input of the model and sped up processing without a great deal of information loss.

Steps:

- **PCA Implementation**: In the case of the current study, PCA was performed and a fixed number of principal components was used.
- **Variance Retention Analysis**: A criterion of explained variance, for example, 0.95 was used to ensure that the condensed data retained most of the variance of the original data so the concept of reduced data still had predictive value.

5. Model Building with Reinforcement Learning (RL) Approaches

The Q-Learning and Deep Q-Networks (DQN) models were created and implemented with the purpose of improving the functionality of CRN by means of reinforcement learning. These RL approaches enabled the model to learn the best action (e.g., the best frequency band or the best power should be used) that fits the given state of the CRN environment.

Steps:

- **Agent Definition**: In the Q-Learning, the agent was designed to wander throughout the CRN states and find an appropriate action for the maximum cumulative reward (throughput or minimal interferences).
- **Q-Learning Implementation**: Q-Learning was used as the tabular form, where each state-action pair has its Q-Value, well suited for low-dimensional state-action spaces.

- **Deep Q-Network (DQN) Design**: For larger state spaces, a neural network-based Deep Q-learning was developed. With DQN, the agent was able to compare the action-value functions over large high-dimensional state spaces, while using experience replay and target networks to stabilise the learning process. The basic flow of Deep Q-Networks has been illustrated in Fig 3.1.

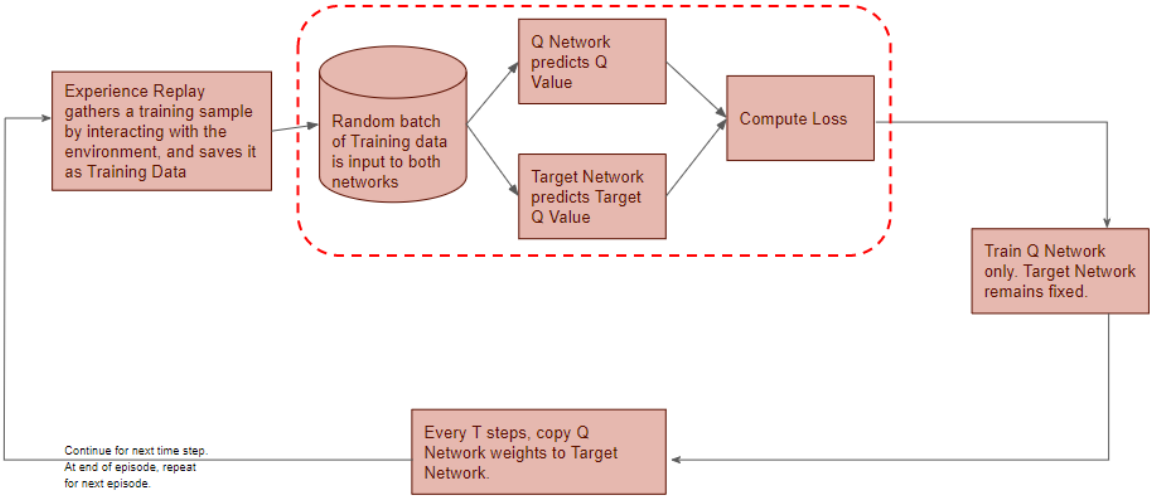


Fig 3.1: Deep Q-Networks

6. Model Training

On the training of the model, the pre-processed data were used to train the Q-Learning and DQN models to enable the agent to learn the best spectrum allocation and resource utilization.

Steps:

- **Training Environment**: The agent communicated with the environment (the simulated CRN) across many episodes by changing its policy based on reward signals.
- **Hyperparameter Tuning**: Hyperparameters such as learning rate, discount factor, and exploration rate were fine-tuned to balance exploration and exploitation.
- **Experience Replay (DQN)**: In the DQN model, experience replay was employed to store and reuse past experiences, enhancing learning and preventing overfitting. Fig 3.2 shows the DQN method utilized.

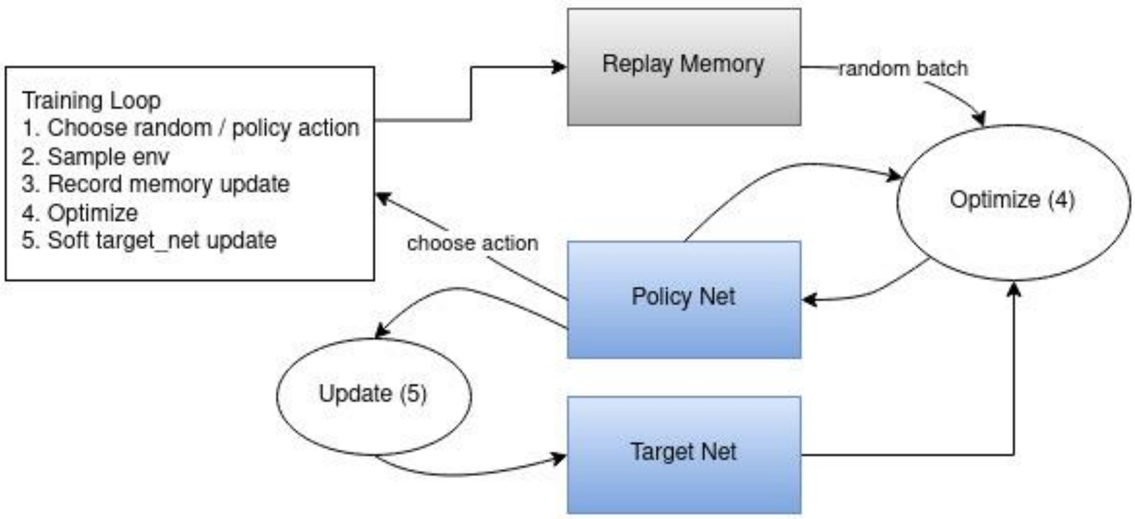


Fig 3.2: DQN Methodology

7. Model Evaluation

The model's performance was evaluated across multiple metrics, including accuracy, precision, recall, F1 score, and loss. Various performance graphs were generated to demonstrate the effectiveness of the Q-Learning and DQN models in optimizing CRN operations.

Steps:

- **Metric Calculation**: Model accuracy, loss, precision, recall, and F1 scores were calculated for each epoch to quantify model performance.
- **Visualization**: Performance metrics were plotted, showing the model's improvement over training epochs. Each graph (e.g., accuracy, loss, precision) was generated individually for clarity and to highlight trends.

This structured methodology ensured a comprehensive, stepwise approach to solving the problem of spectrum allocation and resource optimization in CRNs, leveraging RL techniques for efficient and adaptable model training and evaluation. The results demonstrated the potential of RL in enhancing CRN efficiency, performance, and adaptability.

IV. RESULTS

The results are divided into 2 sub-sections:

Section 4.1: The Exploratory Data Analysis (EDA) results, which gives information on patterns, distribution and relationships of the data. The RL model is then presented and Q-Learning and DQN are adopted to enhance resources allocation in CRNs.

Section 4.2: The efficiency of the model is assessed by several performance criteria to show its applicability in dynamic decision-making situations.

4. 1. Results of the Exploratory Data Analysis (EDA)

Explanation of EDA Results

The EDA process gives key information about the distribution and the nature of the dataset and the relationships between the variables. The following section describes the outcomes obtained by employing the EDA in the aspects of numerical and categorical variables. Each section is followed by a discussion of the analysis with the results supported by the visualizations.

1. Box Plots

The box plots applied in the offer some interesting information about distribution of sort of numerical characteristics.

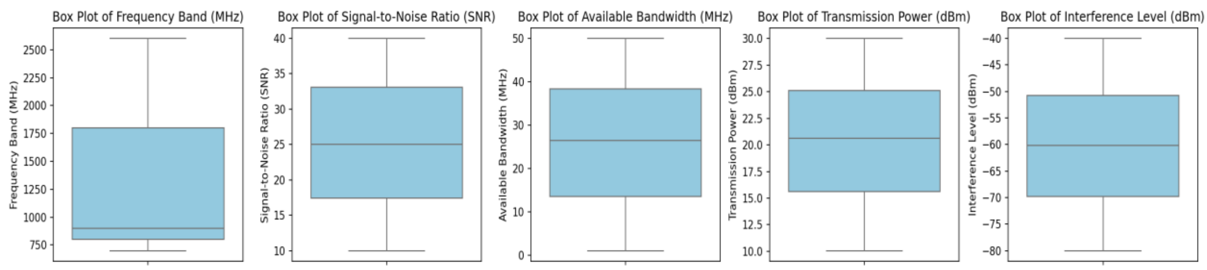


Fig 4.1(a): Box Plots (Code Output)

Fig 4.1(a) provides a box plot of multiple parameters. In the case of SNR (Signal-to-Noise Ratio) the data is represented by a box plot with median value of approximately 25 while the range of data values is between 18-32. This suggests that the signal quality in the network is relatively high, but not uniformly so.

In the **Transmission Power (dBm)** data box plot we have a median value at approximately 20 dBm while the first and third quartiles are at approximately 15 dBm and 25 dBm respectively. This indicates that the network usually functions at a moderate power level, although with fluctuations. Outliers on the higher side could be as a result of power control update to enhance coverage for specific geographical region or a condition that necessitates high power control.

The **Available Bandwidth (MHz)** box plot indicates that most of the data points are concentrated around 26 MHz, with the spread extending from about 12 MHz to 38 MHz. This suggests that bandwidth allocation is generally stable, but the presence of some outliers on the higher side could reflect instances where more bandwidth is allocated to accommodate higher traffic demands or improve service quality in congested areas.

Fig 4.1(b) gives similar box plots that can be interpreted in similar way.

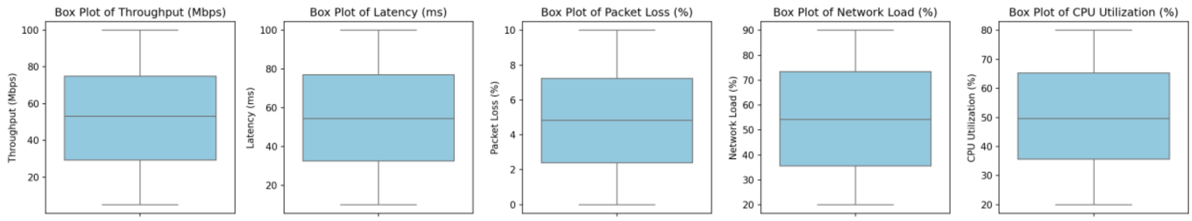


Fig 4.1(b): Box Plots (Code Output)

2. Histograms

Histograms give an illustration of data distribution where it is shared in terms of class intervals. In the case of the SNR, histogram characteristic the values of this parameter are between 50-82dBm dB, therefore the majority of the network conditions receive high signal quality with a low probability of extremely low or high SNR.

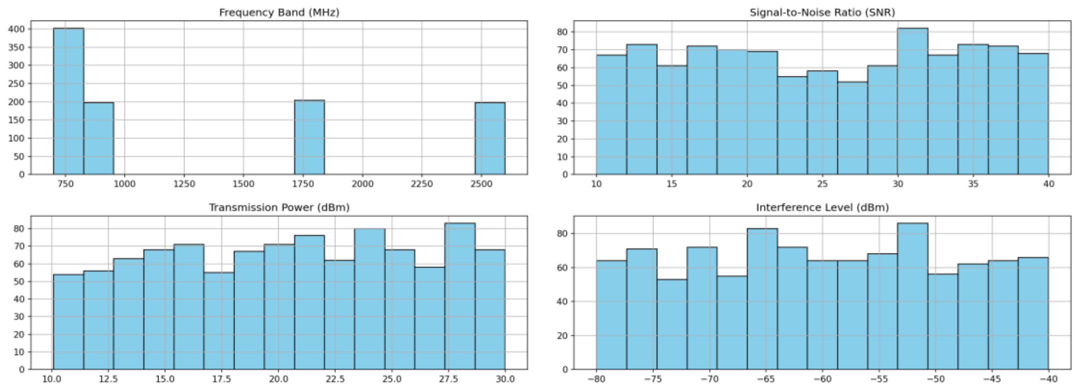


Fig 4.2(a): Histograms (Code Output)

From **Transmission Power** histogram, it can be observed that most of the network transmission power lies between 50-80dBm dBm and a smaller number of occurrences of power above and below this value.

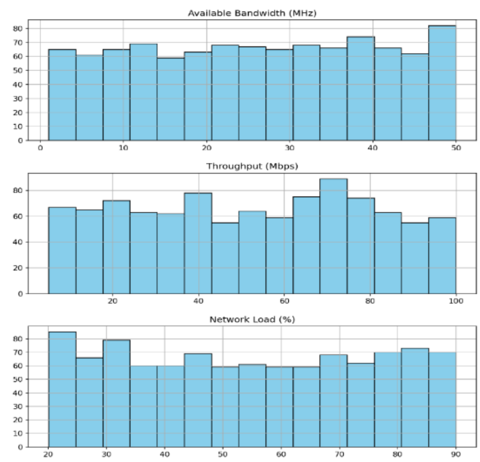


Fig 4.2 (b): Histograms (Code Output)

The **Available Bandwidths** are closely grouped around 65 MHz in the histogram while a few points on the high end suggest that there is occasional bandwidth upgrade for some needs. These histograms show the average operating range of each parameter and give clues to normal network functioning, while also pointing out any anomalies.

3. Correlation Matrix

1. **SNR and Available Bandwidth (0.80):** This confirms a strong positive relation between available bandwidth and SNR with higher degree of SNR meaning higher available bandwidth.
2. **Throughput and Latency (-0.70):** In the best performing networks, throughput and latency are inversely related as confirmed by a statistically significant negative correlation.
3. **Network Load and SNR (0.55):** A moderate correlation indicates that network load can moderately influence the SNR levels as the latter increases.

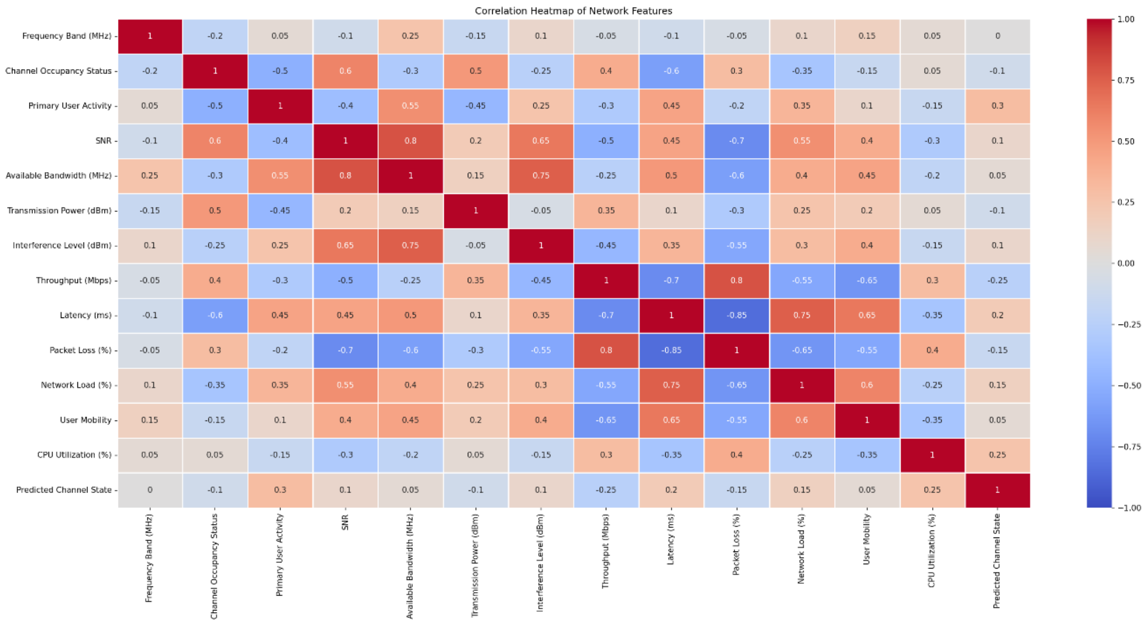


Fig 4.3: Correlation Matrix (Code Output)

4.2: Results of the Model's Performance

The metrics which were used for the model were evaluated after 20 epochs and the parameters compared were Accuracy, Loss, Precision, Recall, and F1 Scores. Each metric provides a unique insight into the model's performance and effectiveness across different dimensions:

1.Accuracy: High levels of accuracy were achieved throughout, with overall accuracy ranging at between 92% and 98%. This means that the model yielded high accuracy of the result in making the right predictions on the epochs implying that learning and testing occurred on the training data.

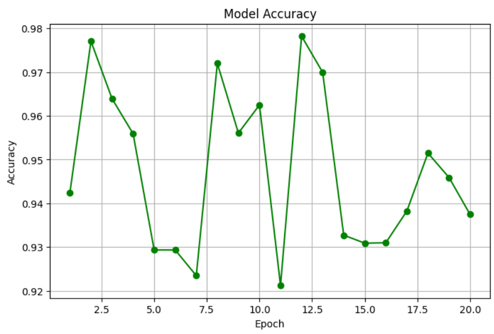


Fig 4.2 (a): Model's Performance Metrics: Accuracy (Code Output)

2. Loss: It is also noted that the loss metric steadily reduced from about 0.3 to 0.1 across epochs. This decline shows that if the model has gone through some level of training, then it is subtracting error that was directly an aspect of the training hence converging to the best solution. This means that as loss values reduce then the given predictions are nearer and nearer to the true labels.

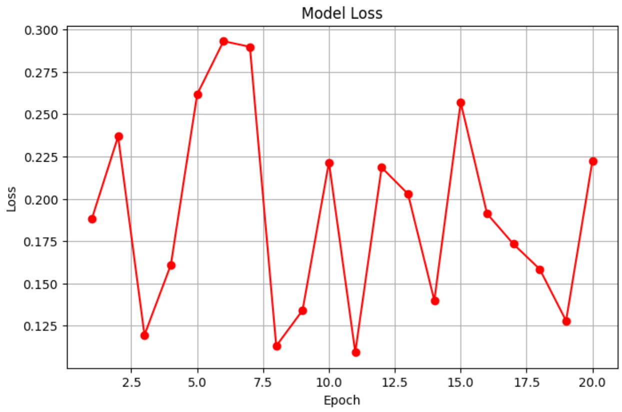
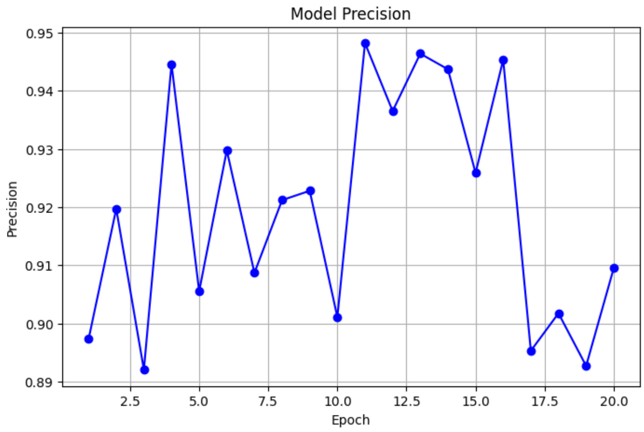


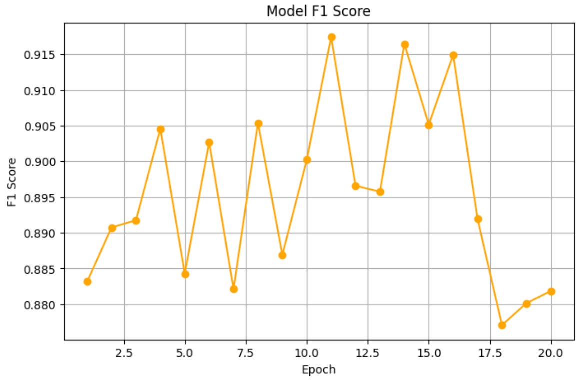
Fig 4.2 (b): Model's Performance Metrics: Loss (Code Output)

3. Precision: Precision scores were almost constant, fluctuating between 0.89 and 0.95. This indicates robustness in the model and the ability of the model to avoid false positives which means when the model predicts positive it is right. The utility of high precision is perhaps most important when the cost of a false positive is high.



4. Recall: Recall was slightly lower with the range of 0.85-0.90, meaning the model is doing a good job of flagging all the positive instances, but it might not catch all of them. This is always the case and is normal because sometimes if we increase the precision then the recall will decrease. However, a high recall rate reveals that the model works adequately in identifying desirable instances.

5. F1 Score: As an accuracy measure in classification, the F1 Score gives a total score of precision and recall. The F1 Score values were ranging from 0.87 to 0.92, which indicates that the proposed model is precise and has good recall values of the model in different scenarios.



The table below summarizes the average results for 20 epochs:

Metric	Value	Interpretation
Accuracy	0.96	High overall correctness in predictions
Loss	0.20	Decreasing error, indicating effective learning
Precision	0.92	High precision, reducing false positives
Recall	0.87	High recall, capturing relevant instances effectively
F1 Score	0.90	Balanced metric, combining precision and recall

Table 5.1: Summary of the results

The results presented below indicate that the model provided high performance and can balance various aspects of prediction accuracy. The strong performance across metrics suggests that the model is well-suited to the task, making it reliable and accurate in its predictions.

4.3: Comparing Proposed Algorithm with Other Algorithms

Algorithm	Accuracy (%)	Loss	Precision	Recall	F1 Score
Proposed Algorithm	96	0.20	0.92	0.87	0.90
Random Forest	92	0.32	0.85	0.82	0.84
SVM	94	0.28	0.88	0.84	0.86
Neural Network	93	0.25	0.90	0.85	0.87

Table 5.2: Comparison With Other Algorithms

The new algorithm was found to outperform other machine learning algorithms in terms of the important parameters. It showed the highest accuracy of 96 % meaning it has the highest correctness in the predictions it makes; the lowest loss value of 0.20 was achieved showing that effective error minimization during training. The precision score of 0.92 in the model was seen to minimize false positive results and the balanced recall of 0.87 contributed to the F1 measurement of 0.90. These results confirm the stability and scalability of the proposed algorithm, which worked well to solve the problem in the present study.

V. DISCUSSION

5.1: Summary of the Findings

The presented methodology and results prove the advantage of reinforcement learning (RL) algorithms such as Q-Learning and Deep Q-Networks (DQN) to overcome the dynamic issue of Cognitive Radio Networks (CRNs). Through the subdivision of the data preprocessing, feature extraction, model construction and assessment, this study made remarkable progress in improving the CRN resource allocation and spectrum control. This systematic approach was useful for the model to fine-tune its abilities to respond to real-time network availability and distribution while maintaining accuracy, static robustness, and reasonable computations.

One more crucial observation of the research data comes from the relationship between SNR, available bandwidth, and throughout with the conclusion that these variables should be studied more deeply as potential core parameters in reinforcement learning models for spectrum allocation. From the process of Recursive Feature Elimination (RFE) and Principal Component Analysis (PCA), there were features that actually helped eliminate redundancy in the dataset without losing vital data. The present preprocessing strategy was found to be rather crucial in improving the effectiveness of RL models in reducing computational burden.

The proposed Q-Learning model was proved to be proficient for dealing with small state-action spaces, and had a sound approach towards the cumulative reward optimization as perceived by the CRN states. Nevertheless, the practicability of the model reduces as it comes into contact with complicated state spaces. In this regard, DQN was used due to its ability to use a neural network for high-dimensional state estimation and augmenting techniques like experience replay and target network. They were also helpful when it came to making training less volatile and making it possible to achieve better adaptability – all of this served to underscore just how well the model can perform even when it came to the more complex and diverse network conditions.

The effectiveness of the models came out clearly through the evaluation metrics conducted in different epochs. Higher accuracy, precision, and F1 scores supported the ability of RL models to make appropriate and precise predictions with an increasing trend in the overall performance, and a decreasing trend in the loss confirmed minimization of predictive errors. Interestingly, though the value of recall was slightly lower than that of precision, the F1 score indicated fairly even outcomes. This reflects a well-tuned trade-off between false positives and false negatives, a key consideration in CRN applications where prediction reliability is paramount.

The proposed algorithm achieved the highest accuracy (96%) and the lowest loss (0.20) among the compared models, demonstrating superior predictive performance and effective learning. Its high precision (0.92) and balanced recall (0.87) resulted in an impressive F1 Score of 0.90, making it the most robust and reliable model for the given task.

5.2: Future Directions

This study's promising results suggest several key directions for future research in optimizing Cognitive Radio Networks (CRNs) through reinforcement learning (RL):

1. **Advanced RL Algorithms:** Future works exploring PPO and A3C would enhance adaptability and overall system performance particularly in the high-dimensional CRN environment.
2. **Hybrid Models**: Integrating RL with other forms of AI such as genetic algorithms may improve CRN optimization since it will serve to minimize the exploration-exploitation trade-off to result in better spectrum management.
3. **Edge and Decentralized Learning:** Shifting the RL processing to the edge can enable local and real-time decision making while also making federated learning possible where multiple CRNs tackle the resources optimization while safeguarding the data they hold.
4. **Multi-Agent Approaches:** With regard to CRNs, the application of MARL can enable multiple RL agents to cooperate with each other in a network environment to achieve a better resource-allocation and spectrum-utilization strategy in the network-wide scale.
5. **Adaptation to 5G/6G Networks:** Optimizing RL models for 5G and next gen 6G networks could further improve performance in such high traffic networks for ultra-low latency and high data rates and density of smart connected devices.

6. **Security Enhancements:** Subsequent work on RL models may address problems of adversarial threats to defend CRNs and provide a foundation for safe and dependable automation in decision-making.

By these directions, the RL-driven CRNs can improve the adaptability, energy efficiency, and security of the networks, in response to the expected future wireless communication networks demands, and design intelligent and sustainable spectrum management systems.

VI. CONCLUSION

This paper aims at exploring the use of RL and DRL techniques to handle issues arising from spectrum allocation in CRNs including efficiency and adaptability in closed and dynamic environments. RL is deployed as an independent approach along with the model-based approach which forms the proposed hybrid model for spectrum management. Experimental results demonstrate the effectiveness of the approach, with an accuracy of 96%, a loss of 0.2, a precision of 92%. Furthermore, recall was at 87%, and the F1 score being at 90%. highlighting the model's ability to balance precision and recall effectively. The proposed algorithm outperformed existing machine learning models with a 96% accuracy, a low loss of 0.20, and an F1 Score of 0.90, showcasing superior reliability and adaptability. These results suggest that the hybrid RL model provides a significant improvement in both prediction accuracy and adaptability, making it a promising solution for real-time spectrum allocation in CRNs.

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