# Development of Sustainable Wireless Resource model through Shrewd Neural Network

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## ABSTRACT

Due to an increasing number of wireless spectrums, the network components are tangling with multiple frequencies and the result create hindrance in resource management process. During resource management process, data leakage is one of the sensitive enigma that requires an astute consideration. Considering all these issues, a sustainable wireless resource management proposal (DSWR-SNN) has been developed by incorporating a shrewd Neural Network. The resources are managed by testing performance of each network component connected wirelessly through dataset testing which matches the results from the dataset corpus. The performance of the proposed DSWR-SNN method has been compared with state of the art studies Hopfield Neural Network (HNN), Radio Resource Management (RRM), and Deep Q-Network (DQN), and results are evaluated by conducting simulation using Python with TensorFlow based on Bandwidth Utilization, Duplicate Packet Handling, Data Leakage, and Energy Consumption. The result illustrates the marvelous performance of the proposed method and effective in addressing the challenges of resource allocation in wireless communication systems.

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## 1. INTRODUCTION

Resource management in wireless networks involves the efficient allocation and utilization of various network resources, such as spectrum, bandwidth, power, and connectivity, to ensure that users and applications receive the best possible service. Network components, including base stations, access points, routers, and switches, play a crucial role in this process. Managing resources in wireless networks will become more complex in the future, such as the management of transmitter power, the design of transmitter and receiver beamformers, and the user management access. With the exponential increase in the number of wireless devices in recent years and the rapid growth of wireless services, it has become increasingly important to allocate and manage the resources astutely. There are still significant challenges in implementation of numerical optimization-based algorithms on practical systems such as, high computation costs, despite the ability to solve specific resource management problems with tremendous results [1].

Several attempts have been made to resolve this high computation time problem using deep learning-based strategies for wireless resource allocation [2]. A first attempt was made in optimization, where weighted minimum mean square error (WMMSE) algorithm [3], was used to map the input and output patterns. Multi-layer perceptron networks (MLPs) [4], accelerates the power allocation process. It is a major concern for machine learning applications to prevent models from revealing sensitive input data details, since neural networks (NN) [5], are known to inherently memorize features of example data while training and to unintentionally reveal them during prediction. However, this is not an easy task. Studies on deep learning-based wireless resource allocation systems that protect privacy are rare in the literature [6].

Due to the dynamic nature of wireless networks, the radio resource management algorithms may not be able to guarantee a reasonable level of performance under all circumstances. An algorithm that learns from interactions with the environment may be able to better handle such dynamics.

Multiple resource management schemes have been proposed to deal with heterogeneous service demands, fairness, starvation, and channel transmission errors [7]. The physical layer also contains timing algorithms, along with power control algorithms, scheduling algorithms, and service advertisement algorithms. However, that many of these schemes prioritize the voice services and allocate the residual bandwidth to applications that are not real-time, where there is no guarantee of delay.

In order to improve the efficiency of network components by measuring the amount of resources being utilized, a shrewd approach is proposed that maximize network throughput by forming coalitions among users and allocating resources based on their transmission conditions. This approach encompasses several network components each connected wirelessly. The network resource of each component is compared with hidden neuron of the neural network where an already established data corpus matches the utilization of the resource. If resources satisfy the system, it sent to wireless resource classification phase where it explores which resource has been used for what purpose and each resource is categorized and named as shrewd outcome. The performance of proposed method is analyzed by conducting simulation in python and results are compared with previous studies such as Hopfield Neural Network (HNN) [8],

Radio Resource Management (RRM) [9], and Deep Q-Network (DQN) [10], on the basis of Bandwidth utilization, Duplicate data packet handling, Data leakage and Energy consumption.

The main contributions are summarized as:

- Using an intelligent neural network, wireless network resources utilization model is formed that test each network component according to its resource utilization behavior.
- The proposed method would significantly improve the network throughput compared to traditional techniques.
- It reduces the resource testing time because it resource is in lined with hidden layer of NN.
- The chances of data leakage have been reduced because each resource is tested with data corpus and neither any ambient data enter into the network nor can be lost.

The rest of the study is arranged as Section 2 presents a comprehensive overview of related work. Section 3 details the proposed method and Section 4 assesses its performance. Finally, Section 5 describes the conclusion and future research outlook.

## 2. RELATED WORK

In the rapidly evolving field of wireless resource management, understanding the current state of exploration is essential for delineating the scope and significance. As technology continues to advance and societal challenges become increasingly complex, the related work aims to critically examine and synthesize the existing body of work in the domain of resource management mechanism, shedding light on key findings, theoretical frameworks, and gaps in the previous studies.

Chang Wook et al. [8], presented a dynamic connection-admission control algorithm for multimedia wireless networks using Hopfield Neural Network (HNN). They developed an algorithm based on two main concepts: Connection Admission Control (CAC) and Quality of Service (QoS) to optimize the use of shared bandwidth resources in a wireless network. The HNN module calculates QoS levels keeping in view the high utilization of the system and fairness in resource sharing. The input values for the HNN are the required bit rates for various types of connections, and the output values are the QoS levels that correspond to those connection requests. These QoS values are then used to make decisions about whether to admit or block connection requests, depending on the availability of bandwidth in the system. The HNN calculates these QoS levels by evolving the state of its interconnected neurons in an unsupervised manner, and converging on a state that corresponds to the optimal solution to the CAC problem. The simulation experiments were conducted using discrete-event simulation software and the results were based on certain assumptions and parameter settings, which may not accurately reflect the behavior of real-world wireless networks because while conducting simulation, authors considered fixed bit rates for different types of connections, whereas in reality, wireless connections can have variable bit rates. Further, in simulation authors only considered network traffic in one cell; a real-world network may have multiple cells and inter-cell interference, which may not be accounted for in this simulation.

Similarly, authors did not explore the energy consumption of the network resources, which could potentially be a significant factor in the design of wireless networks.

Radio resource allocation problem in wireless communication has been discussed by Jens Zander et al. [9], by considering three basic allocation decisions: waveform, access port, and transmitter power. They explored the challenges posed by future systems, such as high bandwidth requirements, types of traffic like bursty and mixed traffic, and the need for dynamic resource allocation to handle variations in signal quality and interference. Authors also highlight the need for efficient spectrum management due to the increasing demands for high-speed multimedia communications. They mentioned the trade-off between maximizing resource utilization and obtaining reliable quality measurements for efficient adaptation of radio resources to user needs. However, authors did not provide detail information about the specific resource management algorithms or techniques. Even they did not go into depth about how these concepts are implemented or their effectiveness in real-world scenarios.

In order to select the best channel for wireless communication between devices Dominik Neznik et al. [11], developed an algorithms for channel allocation in the D2D network where they explored the use of Game Theory and Fuzzy Logic principles to improve channel allocation and enhance the quality of links for communication. Each method works autonomously on every device in the network. The process involves parameter initialization, spectrum sensing, and communication between devices. The final channel allocation is determined based on the last iteration of each method. The Fuzzy Logic method is considered more suitable for channel ranking due to its precision in ranking each channel based on membership functions. The Game Theory method involves devices cooperating to improve the quality of the network. Further, they worked out to optimize the network's performance by considering factors such as RSS value, SIR value, and traffic value. However, this method requires more iterations to evaluate optimal channel selection. This longer evaluation time can impact the efficiency of channel allocation management. Furthermore, it requires more computational resources which is a major disadvantage in resource-constrained environments or even for devices with limited processing capabilities.

Thong-Nhat Tran et al. [10], proposed method for QoS multicast routing in cognitive radio mobile ad hoc networks (CR-MANETs). The model was consist of two sub-problems: the Minimum E2E Cost (MEC) problem and the Channel-Time Slot Allocation (CTA) problem. The DQN-MEC model is designed to predict optimal Q-values for selecting the best neighbors, while the GT-CTA model selects optimal channel-time slot strategies. The document also provides analysis of E2E queuing delay in different mobility models. However, in order to reduce the time and resource consumption in the routing process, the authors did not focus on developing Q-learning models that can be updated online continuously and it can ensure that the models adapt to the frequent movement of mobile nodes in MANETs. In addition, authors addressed the channel-time slot allocation problem in the context of QoS multicast routing in Cognitive Radio MANETs and demonstrated through numerical results that the GT-CTA model achieves the optimal solution with small iterations however, without showing proper results how it can be validated is a big question!

An overview of each study covered during the literature search is presented in Table 1, along with a possible solution to the problem.

**Table 1.** Summary of the related work, comparison and the proposed solution.

| Studies | Expediency ground | Subject Region | Strategy | Impairments | Proposed Solution |
|---|---|---|---|---|---|
| Chang Wook et al. [8] | maximizes resource utilization and minimizes blocking probabilities in wireless networks | Wireless communication | quality-of-service (QoS), dynamic connection-admission control (CAC) | Algorithm require significant computational resources | Through dataset testing and dataset corpus, the resource utilization is measured. |
| Jens Zander et al. [9] | RRM for channel allocation, power control, and admission control to improve the performance of wireless networks | Telecom and wireless networks | efficient spectrum/ radio resource management | impact of propagation conditions | Performance of connected devices are measured through resource classification. |
| THONG-NHAT TRAN et al. [10] | QoS multicast (EQM) trees by addressing queuing size ratio, link stability, number of hops | cognitive radio mobile ad hoc networks | optimization problem to find feasible solutions for EQM trees | Discuss the Inadequate Q-Learning | Using intelligent neural network, each network component is tested according to resource utilization behavior. |
| N .D. Navghare [12] | using homomorphic encryption and neural network learning to preserve data privacy and improve prediction accuracy | data privacy, prediction using neural networks, homomorphic encryption, and cloud computing in the context of collaborative learning and prediction scenarios. | practical application of collaborative learning, data privacy preservation, and prediction accuracy | Training time for encrypted data is higher compared to plaintext data | Chances of data leakage because each resource is tested with data corpus and neither any ambient data enter into the network nor can be lost. |

**Table 1.** *Continued.*

| Studies | Expediency ground | Subject Region | Strategy | Impairments | Proposed Solution |
|---|---|---|---|---|---|
| Dominik Neznik et al. [11] | optimize the channel selection in wireless networks to improve the quality of device connections | Wireless communication | Game Theory as a strategy for channel allocation in wireless networks | large interference in wireless communication | The performance of connected network devices are optimized. |
| Mark Eisen et al. [13] | resource allocation using machine learning tools in wireless communication | Wireless communication | leveraging DNNs, model-free algorithms, and the Lagrangian dual formulation | uncertainty in measuring the radio environment | Resource configuration is analyzed using neural network. |

## 3. PROPOSED ARCHITECTURE

Resource management process in wireless networks has become an indispensable feature for future networks. The data transfer mechanism faces an aggravate situation due to unsecure wireless networks which ultimately prone to invite intruders and as a result, network becomes bottleneck. In order to deal with this situation, a sustainable wireless resource model has been developed by adopting a Shrewd Neural Network. The network resources (NR) [14], oriented mechanism has been developed where numerous network resources such as $nr_1$, $nr_2$, $nr_3$, $nr_4$……..$nr_n$ have been considered as illustrated in figure 1. Specifically, these network resources may encompasses computer nodes, routers, switches, firewalls, monitoring applications, and the protocols by which the data transfer takes place. The performance of each network resource is tested from an already available dataset. This dataset deals each resource through hidden layers of neural network such as $a_1$, $a_2$,….$a_m$ which finally yield the authentic data in the logical form either zero or one (Y or Z). This logical yield vouches that relevant resource is being operated at appropriate place and no any rover data from an anonymous source is interfering. A dataset corpus consisting of Y and Z builds automatically for each resource. If received data from relevant source such as Y or Z matches to relevant entity in the data corpus then it would forward to wireless resource classification phase where it performs the classification tasks over the received data, otherwise it would return to the beginning of Dataset testing phase.

### *3.1 Architecture description*

The data relevant to network resource such as DNR = ($dnr_1$, $dnr_2$, $dnr_3$, $dnr_4$……..$dnr_n$) of any size is considered. Initially, to validate the dataset each data source ($dnr$) makes a mutual association with

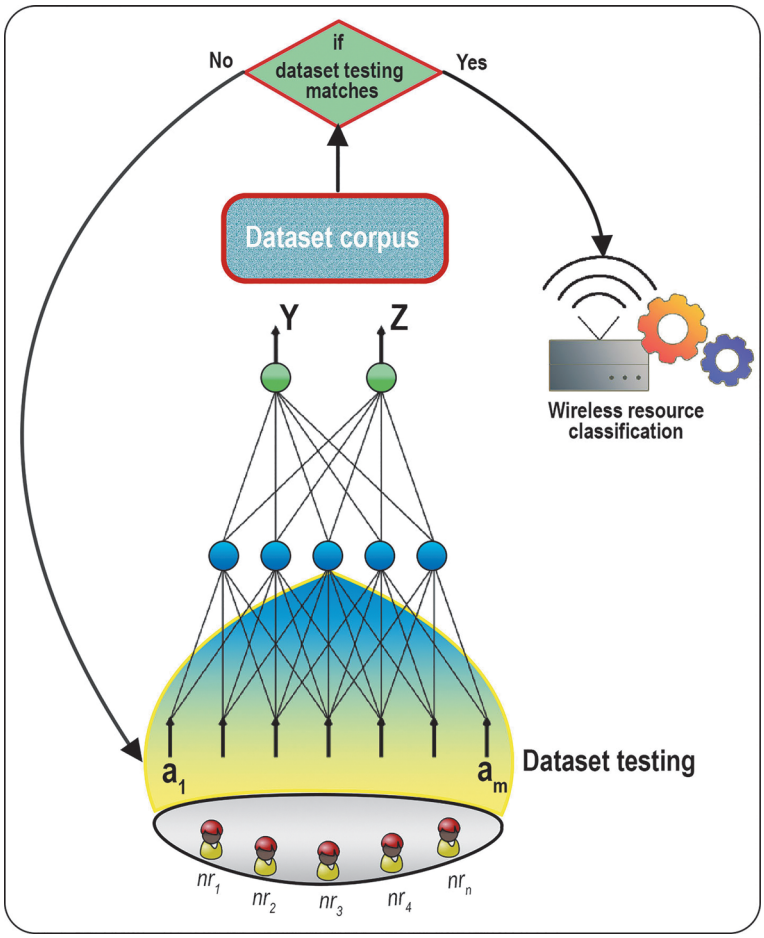



**Figure 1.** DSWR-SNN architecture and network resources are under evaluation.

relevant hidden layer of the of neural network such as, $a_1$, $a_2$,….$a_m$ respectively. The outcome of mutually tested data is categorized according to correct match either zero or one (Y, Z). At this stage, it verifies no data other than placed equal to Y and Z would be accepted. Consequently, the chances of any data leakage of any resource would be mitigated. Similarly, tested yields of Y and Z are further verified against already available resource dataset and it pass this test ultimately, the data is transferred to the wireless resource configuration section.

It is amazing how neural networks find the components that actually manage the resources during operations, ensuring that no irrelevant components are included in the resource management process. Signals are transmitted between artificial neurons through a set of nodes. From input to output, these signals are transmitted. A predicted output is obtained by propagating and analyzing data via the hidden layers [15], of the neural network. The neural network is trained using backpropagation, which involves

propagating the error between the desired and expected output into the next layer, at which point the neuronal connections' weights are modified to minimize the error.

Neurons are modeled as nonlinear devices that operates in heterogenous network environment. with a sigmoid $f_i$ monotonically increasing function defined by the logistic function given in Eq.1

$$V_n = f_n(U_n) = \frac{1}{1+e^{-\alpha_n U_n}} \tag{1}$$

where $U_n$ is the input of $n^{th}$ neuron, $V_n$ taking on any value between 0 and 1 is the output of $V_n$ neuron, and $\alpha_n$ is the gain of the device on the $n^{th}$ neuron. Each neuron receives resistive connections from other neurons and these connections can be fully described by the interconnection matrix $T = [T_{nm}]$. Here $T_{nm}$ is the interconnection weight from the $m^{th}$ neuron to the $n^{th}$ neuron. Each neuron also receives an input bias current $I_n$. After making an adjustment the parameters are set as Eq. 2

$$\frac{dU_n}{dt} = \sum_{k=1}^{L} T_{nk} V - \frac{U_n}{\tau} + I_n \tag{2}$$

where $\tau$ is the time constant of the network and $L$ is the number of neurons. In wireless communication, the interference channel plays an important role during transmission. In order to determine how neural network is efficient over interference channel, consider that $P$ transmitters are communicating with base station whereas fading channel is given as $h = [h^1; \ldots\ldots h^m]$. The network capacity is determined signal-to-noise-plus-interference ratio (SNIR), which for transmission $n$ is given as Eq. 3

$$SNIR^n = \frac{h^n p^n(h)}{V^n + j^m p^m(h)} \tag{3}$$

At the receiving end, the received network resource is given as Eq. 4

$$f^n(P^n(h), h) = \frac{\log(1 + h^{nn} P^n(h)}{V^n + h^{mn} p^m(h)} \tag{4}$$

Three different networks such as $n_1$, $n_2$ and $n_3$ are connected through wireless link and each consists of the mix of various devices illustrated in figure 2. The resource management process would verify each of these devices by taking into account through dataset testing phase.

In this phase, Resource management costs are minimized by creating training data first, then assigning them labels. An NN is nothing more than an intelligent switch for the payload that changes configurations immediately when the system requirements change *i.e.*, the impact of a delay in updating resources on capacity is negligible. NN performance during training is crucial, and it is also important to avoid overfitting, as this will depend on resource management.

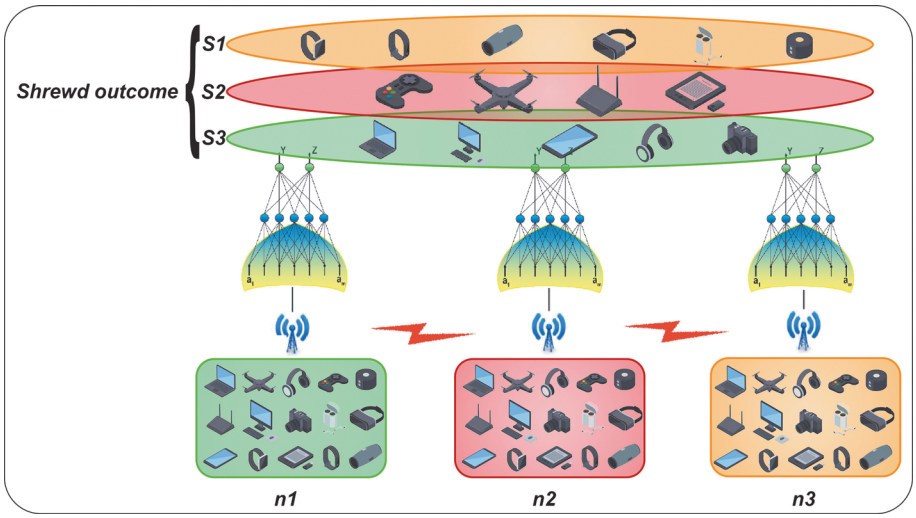



**Figure 2.** Resources are being classified.

$$J\left(\hat{\boldsymbol{Y}},W\right)=-\frac{1}{m}\sum_{n=1}^{m}[\boldsymbol{Y}^{(\boldsymbol{n})}.log\hat{\boldsymbol{Y}}\left(\boldsymbol{X}^{(\boldsymbol{n})}\right)+\left(1-\boldsymbol{Y}^{(n)}\right)log\left(1-\hat{\boldsymbol{Y}}\left(\boldsymbol{X}^{(\boldsymbol{n})}\right)\right)]+\frac{\lambda}{2m}\sum_{m'=1}^{k}W \tag{5}$$

It is also worth mentioning that system will respond to changes in traffic demand by modifying two wireless resources. The training dataset is generated with different possible traffic demand. The label indicates which configuration of the resource allocation set minimizes the cost function given in Eq. (5) for each of these possible combinations of the required capacity at each layer, where $m$ shows the number of training samples, $\boldsymbol{X}^{(\boldsymbol{n})}$ indicates the $n^{th}$ training sample with possible required capacities in each device. During testing phase, it would become $\boldsymbol{X}^{(\boldsymbol{n})}=\left[\boldsymbol{X}_{a_1}^{\boldsymbol{n}},\boldsymbol{X}_{a_2}^{\boldsymbol{n}},\boldsymbol{X}_{a_3,\ldots\ldots\boldsymbol{X}_{am}}^{\boldsymbol{n}}\right]$, $\boldsymbol{Y}^{(\boldsymbol{n})}$ represents the $n^{th}$ configuration corresponding to $\boldsymbol{X}^{(\boldsymbol{n})}$, $\hat{\boldsymbol{Y}}\left(\boldsymbol{X}^{(\boldsymbol{n})}\right)$ is the configuration predicated for $\boldsymbol{X}^{(\boldsymbol{n})}$, $k$ is the order of logical regression and λ is the regularization parameter to avoid overfitting. The goal of logistic regression is to optimize all log losses for all observations, which is equivalent to optimizing cross-entropy on average.

The dataset testing analyze each device according to the resources it utilize during operation. The devices that utilize similar resource are categorize in same corpus and the creation of new networks are formed. This time each newly created network contains the devices having same attribute and these networks are named as $S_1$, $S_2$, and $S_3$. These networks are the outcome of the shrewd resource management elements because during dataset testing process the devices with only valid resources would be given the access while rest would be blocked. Consequently, the networks came up with shrewd resource configuration process.

## 4. PERFORMANCE AND DISCUSSION

In order to validate the proposed method, simulation has been conducted using Python 3.6.9 with TensorFlow 1.15.0. The validation of resources have been performed between dataset testing and dataset corpus. The results have been obtained on the basis of Bandwidth utilization, Duplicate data packet handling, Data leakage and Energy consumption. Resource allocation decisions are optimized based on task attributes and resource status. Within a selected area, various number of devices have been taken into account. Each device has a fixed number of $\tau$ scheduling intervals as discussed in Eq. 2.

The total number of 50 different devices have been considered for this experiment. As the data traffic rovers among devices through different routes, the dataset of each device is tested from dataset corpus. Each device handles data traffic from source to destination. The variation in devices effect to the overall execution time is evaluated. The performance of proposed method is being analyzed in two steps. In first step, device performance is analyzed. While in second step, Resource utilization is tested. At the beginning of the simulation, state transition probability matrices are measure for computing, caching and communication status. The outcome of the proposed method is compared with state of the art wireless resource management techniques such as Hopfield Neural Network (HNN), Radio Resource Management (RRM), and Deep Q-Network (DQN). This experiment focused on high utilization and fairness of allocated resources without blocking or dropping connections in the simulation environment.

### *4.1 Bandwidth Utilization*

It refers to the extent to which available wireless network bandwidth is being used by various devices to transmit data. It is a measure of how efficiently data is being transferred over a network connection. The bandwidth utilization of proposed method (DSWR-SNN) has been tested with other methods illustrated in figure 3. Overall, 50 network devices were used for this experiment. It can be seen that DSWR-SNN, utilizing maximum bandwidth at the beginning of the simulation. With the increasing number of devices, when data traffic reaches at its peak, its bandwidth utilization decreases gradually because all devices are fully routing the data packet and it only utilize a modicum path. It also evaluate the expected bandwidth and packet delay of each device aiming to achieve better balance network traffic. It is worth noting that this situation presages the relationship between energy consumption and transmission rates, which are determined through channel allocations. In addition, it could finds efficient bandwidth allocations even for large-size networks while maintaining the truthfulness property.

While comparing the performance of HNN, that started with 70% and reduced near to 31% of the bandwidth utilization at device 50. It is because each neuron is modeled as a nonlinear device with an input and output values. It attempts to maximize the utilization of shared resources.

Further, considering RRM, the bandwidth utilization seems none linear and fluctuates from device 20 to 40. It achieved maximum theoretical throughput and at device 50, the utilization remains at 37% that vouched its untrust performance because effective spectrum allocation to devices is not available. Though, it manages the parameters like power, frequency, and channel allocation to provide maximum

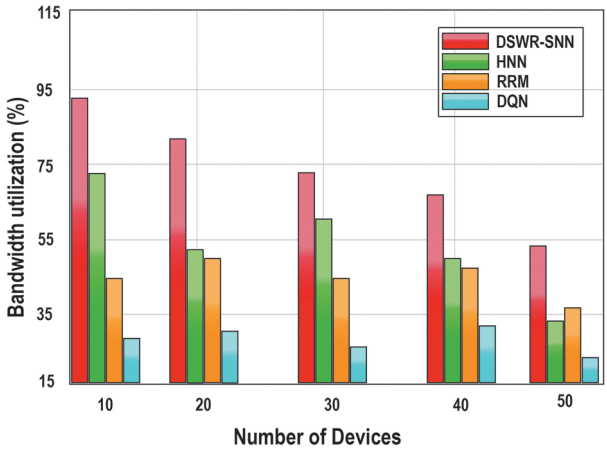



**Figure 3.** Comparative analysis in terms of bandwidth utilization.

possible efficiency but issues concerning the dependability of the components make its performance compromising. At the other hand, DQN utilize very less bandwidth and could not carry entire traffic because it uses deep neural networks, which have large model size and transmitting the model parameters over a network consumes huge bandwidth but not for network traffic.

### *4.2 Duplicate Packet Handling*

It deals with the issue of receiving the same packet more than once at the receiving end. This issue arise due to various reasons, such as signal reflections, and retransmission overlapping of multiple neighboring nodes. Figure 4, reveals the statistics of entire network. At the beginning, the generation of duplicate packets were very low but detection of these packets was very high by the proposed DSWR-SNN method. Reaching to 50 devices, this detection remains high which shows that how efficiently it utilize the resources and pointed out the flow of duplicate packets which would handled in other phase. The proposed method utilized the labeled dataset of packets where each packet is associated with a label indicating whether it's a duplicate or not. This dataset include features derived from the packet content, such as packet payload, and headers. Further, it splits the dataset into a training and a testing set. The performance of HNN, RRM, and DQN remain scanty because these methods do not utilize the neural network.

### *4.3 Data Leakage handling*

It refers to the unauthorized or unintended disclosure of sensitive information during the resource allocation process. This result verify the detection of such data by the proposed DSWR-SNN and other systems.The proposed DSWR-SNN method is enough trained to detect the data leakage during packet transmission. The transmitted data from one device to another is examined from dataset testing to dataset corpus, if the match could not validate the received data with dataset corpus it labeled it and

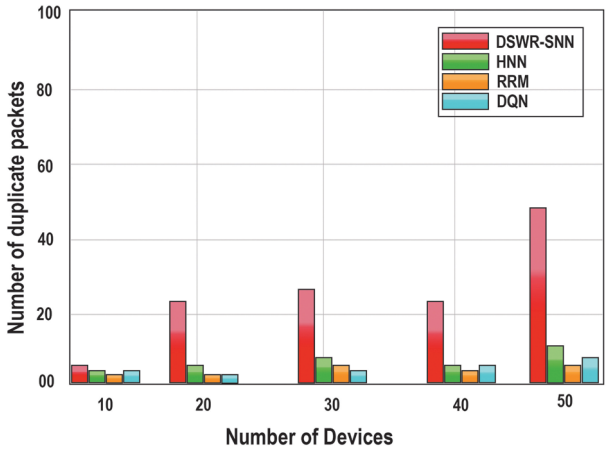



**Figure 4.** Duplicate Packet Handling.

anomaly therefore, no ambient data would be transmitted and no chance of data leakage would occur. It can be seen that DSWR-SNN detected the maximum amount of data leakage whereas other systems didn't achieve this level of detection. Comparing the performance of HNN, which is a recurrent neural network that used to solve optimization problem and demands extremely large search space for solving optimization problems. When search space becomes unmanageable due to the combination of multiple service it can not handle each neuron and therefore degrade the packets and can not detect the entire data pool. Therefore, result shown in figure 5, vouches that at node 10 its detection was 50% and reached at maximum when reached to node 30 but receiving data from other devices made it vulnerable to handle it and its leakage detection becomes modicum. Due to an increase of interference, RRM can not mitigate the chances of data leakage. Interference lead to reduce signal quality which consequently, give space to the unauthorized anomaly to enter and breach the data secrecy. It can be seen that from node 10 to 50, as network grows the data leakage detection has been decreased. Considering the outcome of DQN, through its detection ability remained much better than RRM, and HNN but as it happened with other systems that its performance decreased as the network overload becomes complex. Consequently, at node 50, its performance reached emaciated to all others. This is because it works in non-stationary environment that can be changed over time. DQNs might not adapt well to such changes without further modifications and it requires significant memory and storage resources to store the large neural network models and experience replay buffers, which can be a constraint in resource-limited environments.

### *4.4 Energy Consumption*

It is the amount of energy consumed by the devices during data transmission in entire network. The output result shown in figure 6, ouched the performance of all studies. The proposed method utilized a maximum of 18% during entire operation and its utilization remained linear whereas other systems didn't

follow any proper consumption mechanism and DQN consumed maximum energy at node 20 which is more than 90%. The performance of HNN and RRM seems not good enough due to non-linear and dynamic nature of training phase where network adjusts its synaptic weights to store patterns and energy consumption during training depends on the hardware pattern.

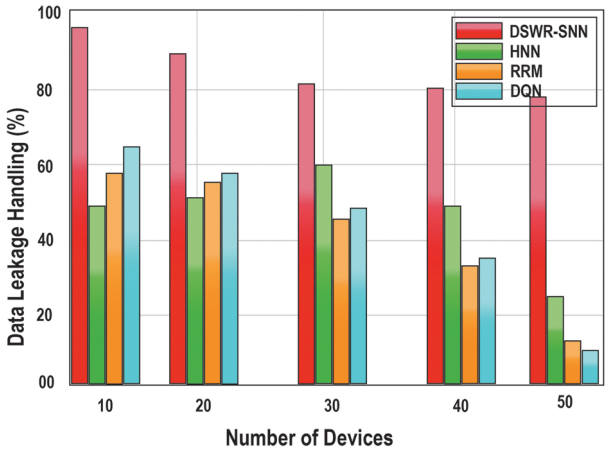



**Figure 5.** Data leakage handling.

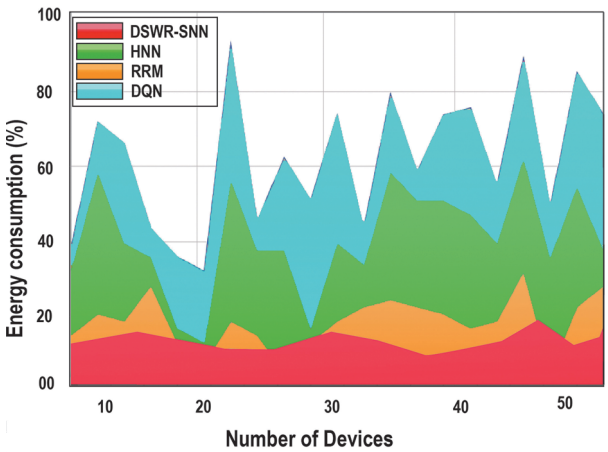



**Figure 6.** Energy Consumption.

## 5. CONCLUSION

A sustainable wireless resource management model DSWR-SNN has been developed using neural network. The outcomes are compared with Hopfield Neural Network (HNN), Radio Resource

Management (RRM), and Deep Q-Network (DQN) by considering the Bandwidth Utilization, Duplicate Packet Handling, Data Leakage, and Energy Consumption. According to the obtained statistics, the proposed method utilized full bandwidth to ensure that network component operates at maximum capacity. However with an increasing number of devices and the presence of multiple protocols the bandwidth utilization capacity decreases but comparing with rest of the studies it came up with better outcome. A similar trends was seen for Duplicate Packet Handling, Data Leakage, and Energy Consumption. For future research, the frequency reuse concept is planned to implement during resource management process.

## AUTHOR CONTRIBUTIONS

SHAHZAD ASHRAF: Conceptualization

Furqan Memon: Data acquisition

Fouzia Akram: Supervision

Zeeshan Rasheed: Analysis

Shahzad Sarwar Bhatti: Proof reading

Innam Ullah: Testing

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## SUPPLEMENTARY MATERIAL

Any relevant content can be requested from the corresponding author.

## CONFLICTS OF INTEREST

On behalf of all authors, the corresponding author states that there is no conflict of interest at all.

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