# Artificial Intelligence with Machine Learning Model for Resource Management in Wireless Networks

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**ABSTRACT**

Artificial Intelligence (AI) improves resource management and energy conservation through machine learning, improved forecasting, and quicker data processing. Artificial intelligence (AI) and machine learning (ML) have become essential enablers of this integration in this context. Machine learning and artificial intelligence are necessary for an organization's survival and expansion, not just a choice. This research explores the growing significance of machine learning and artificial intelligence in resource management. The proposed method, deep reinforcement learning (DRL) based on machine learning is an essential tool for addressing the issues of resource management. Resource management can ensure that certain QoS criteria are met for various applications, such as information or real-time video transmission. Reducing total transmit power allows optimal resource management, while following Quality of Service (QoS) criteria permits a better relay choice. In this paper, the numerical results show that it performs competitively in terms of bandwidth of 97.5%, power consumption of 96%, spectrum efficiency of 91%, and network lifespan of 93 percent. Costs are decreased and environmental responsibility is enhanced through resource management. This research examines how AI might increase bandwidth, power consumption, spectrum efficiency, and resource management, with a particular emphasis on automation, efficiency, and prediction via quality of service.

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## 1. INTRODUCTION

Artificial Intelligence (AI) improves resource management and energy conservation through machine learning, improved forecasting, and quicker data processing. Resource management has to be dynamic since the actual server's load varies over time. Dynamic resource management is quite challenging, mostly when QoS must fluctuate constantly while taking processor availability and idle time into account. One of the most important subjects to discuss while handling DRL scenarios is resource management [1]. AIML has been utilized to address many mundane and intricate issues that arise in resource management and wireless network management. By making the most use of the resources at hand, AIML techniques improve network productivity and reduce computing time.

Machine learning methods for wireless network resource management offer a unique opportunity to address significant issues and create efficient, dispersed, self-sufficient networks. Using trial and error, reinforcement learning (RL), a fundamental AI method, determines the best course of action to optimize long-term aggregate benefits without the need for previous modeling of the changing and complicated environment [2]. Machine learning (ML) techniques are renowned for not requiring retraining and self-experiencing. ML is a practical method that makes processing reliable, efficient, and affordable. The three primary types are supervised learning, unsupervised learning, and reinforcement learning. Techniques developed using machine learning (ML) can offer a better method for allocating network resources. Algorithms for resource management based on machine learning are created to examine and model how human decision-making processes behave. The program uses machine learning (ML) technology to make real-time judgments based on environmental patterns seen from high-resolution data inputs [3]. The program can measure the effects of several characteristics, such as user load and channel state, on performance and rapidly determine which resource allocation techniques will produce the best results.

AI and machine learning have such a profound influence on many areas of society, the economy, engineering, technology, and science; they may be very inspiring and fulfilling. When applied to wireless networks, machine learning algorithms produce creative solutions that tackle WN issues. By making the best use of the network's resources, adaptive resource administration systems increase wireless network efficiency [4]. Effective solutions for using Artificial Intelligence (AI) in Resource Management are examined in this study using a qualitative methodology, with a focus on employee experience customization, security and privacy, and technical adaptation [5].

Effective resource management is essential for wireless networks. By preventing limited resources, this administration should improve the quality of service (QoS) and Quality of experience (QoE) for users. It is feasible to enhance wireless network resource management and user quality of service by forecasting the number of connected users. Resources like bandwidth may be controlled, and APs can be turned on or off based on the anticipated quantity [6]. Network devices may be managed in this way to control user relationships between APs and save energy. This demonstrates how Deep reinforcement Learning is an example of Machine Learning, a subset of artificial intelligence. Artificial intelligence is a broad concept that encompasses the creation of autonomous agents, which are systems that can observe their environment, learn, reason, and take action to achieve objectives [7].

Deep learning is a subfield of machine learning that uses several layers of artificial neural networks to understand intricate data patterns. Machine learning algorithms may examine previous information on economic indicators, geopolitical tensions, and news mood to predict possible problems. This enables companies to make proactive adjustments to their supply chain plans. Even if they aren't always as good as theoretical answers, machine learning models trained on optimum solutions can make effective daily judgments. One of artificial intelligence's primary technologies, reinforcement learning (RL), uses trial and error to determine the best course of action to optimize long-term compounding rewards without the need for previous analysis of the dynamic and complicated environment [8]. A federated RL algorithm was also suggested to maximize the time-frequency resource management and enhance the quality of service (QoS).

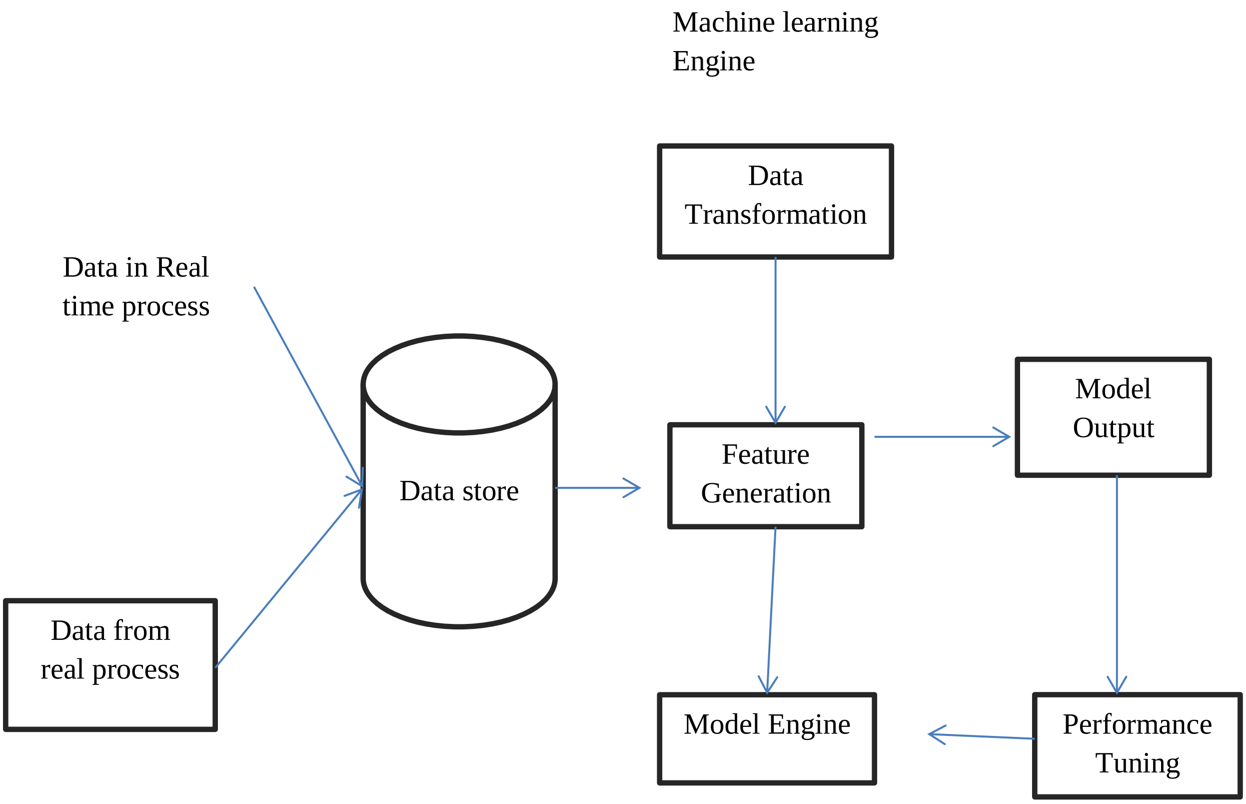


Figure 1. Machine Learning Construction

## 2. LITERATURE REVIEW

Alhussien et al. [9] proposed Toward AI-Enabled Green 6G Networks: A Resource Management Perspective. Network resource management, demand for energy balancing, EE optimization, and Energy Harvesting (EH) integration may all be accomplished with AI approaches. To increase connectivity, optimize the distribution of resources, and reduce energy usage, this article looks at 6G infrastructure from an AI viewpoint. Investigated are AI models for effective resource use to improve network and EE efficiency. It has been demonstrated that AI is essential to attaining green RM in 6G networks. To address the increasing needs and new obstacles, future fields of study for intelligent networks are described.

Eldeeb et al. [10] introduce wireless communication based on Offline and Distributional Reinforcement Learning. While both machine learning (ML) and artificial intelligence (AI) have shown promise in this field, real-time wireless systems present challenges for firmly RL and classic online reinforcement learning (RL) techniques. Online interaction might be unsafe, costly, and unfeasible. To overcome the disadvantage we introduce offline and distributional reinforcement Learning.

Zhang et al. [11] introduced a New Paradigm Resource Management Decision Transformers for Wireless Communications. An essential technique for solving stochastic optimization problems involving resource management is deep reinforcement learning (DRL). When conditions and movement spaces change, DRL must restart every training procedure, which results in low sample efficiency and weak generalization capacity. In this paper, we use Decision Transformer (DT), a different AI technique, and provide a flexible solution framework for wireless resource management that depends on DT. The proposed method is used for DT frameworks for two communications: Communications facilitated by intelligent reflecting surfaces and mobile edge computing facilitated by unmanned aerial vehicles. The proposed method shows that the suggested DT approaches outperform the traditional DRL approach, proximal policy efficiency, and attain resolution speeds of over three to six times.

Han et.al [12] proposed the moderating effect of executive traits and eco-friendly alignment of sophisticated resources with artificial intelligence. With the development of artificial intelligence (AI) technology, businesses are beginning to view AI as a strategic need. Data from surveys of 717 executives from multinational companies were used to evaluate theories. According to the study, the link between AI orientation, innovation collaboration systems, and internal creativity resources might be adversely moderated by environmental uncertainty (EU).

Barker et.al [13] designed a Leveraging Artificial Intelligence and Machine Learning for Wireless Systems based on open-RAN and mobile edge computing. The proposed method mainly used for two revolutionary methods for making the future of wireless communications are mobile edge computing (MEC) and open radio access networks (ORAN). In this paper, we focus on how difficult wireless problems have been resolved by applying machine learning (ML) and artificial intelligence (AI) approaches. To improve network flexibility, ORAN uses AI/ML to create smart xApps for planning, cutting networks, and online training. The proposed method discusses the techniques and shows how these technologies enhance system scalability and efficiency.

Eldeeb et.al [14] introduced Radio Resource Management using an Offline Multi-Agent Reinforcement Learning Framework. In this work, we provide an offline MARL method for radio resource management (RRM), with an emphasis on programming policy optimization for multiple access points (APs), to simultaneously optimize both the total and peak speed of user equipment (UEs). The proposed method shows that the offline MARL structure executes better than traditional beginning methods, improving a weighted set of sum and tail rates by more than 15%. Meanwhile, the CTDE structure effectively balances the weaknesses of individual training with the computational difficulties of centralized methods. The result shows the ability of offline MARL to provide resource management solutions in dynamic wireless networks that are scalable, reliable, and effective.

Ning et.al [15] developed a Hierarchical Architecture for Managing Resources in Networks of Connected Construction Equipment Using Diffusion-Based Deep Reinforcement Learning. The digital change of building tunnels is happening very quickly. Construction equipment (CE) may collaborate on operations by integrating strong direct connections, which enables real-time data sharing. To address the issue, using the process of construction coherence degree (CPCD), which depends on the age of information (AoI), we match communication's quality of service (QoS) to efficiency during construction and provide a multilevel resource management system. The proposed methods show that related to other benchmarks, the findings demonstrate higher efficiency in terms of CPCD content and prove the efficiency of the DSAC-QMIX technique with an equal transmission rate.

## 3. METHODOLOGY

Deep Reinforcement Learning (DRL) has become a viable approach to complicated decision-making issues. The RL agent's main goal is to maximize the benefit by identifying the best course of action. Learning systems that are strengthened make an effort to strike a balance between exploration and extraction. DRL provides a data-driven structure for enhancing cloud video conferencing service selections while accounting for real-time system circumstances and efficiency feedback. By combining reinforcement learning and deep neural networks, DRL communicates with the environment to determine the optimal rules [16]. Deep RL algorithms, among the most popular, change the agent's behavior policy using neural networks. SARSA and Q-Learning are the two most popular reinforcement learning algorithms. Due to its near resemblance to human natural learning, reinforcement learning is ideal for conversation systems as it can provide responses that make sense in context.

### Deep Reinforcement Learning Architecture

Reinforcement Learning strategies create logical and engaging conversations by modeling future rewards and optimizing long-term goals. To learn the model, a conversation between two agents is simulated. The system creators provide long-term incentives, which are determined by elements like the conversation's coherence, participation, and informativeness [17]. The agent explores the universe of options to maximize the reward. The conversations a person can produce are in the action space, and the dialogue history is in the framework of the state space.

The management policy of the agent determines the stochastic description of an LSTM encoder-decoder. It is the collection of every action or movement the agent can do. Out of a range of distinct actions, the agent can perform (a). The environment is immediately impacted by every action the reinforcement learning agent does. The environment returns the reward to the agent in a new state after using the agent's current state and action as information [18].

Figure 2, shows that the models for information flow, semantic coherence, and simplicity of replying are used to determine the rewards. Artificial intelligence agents discover on their own how to employ effective tactics that provide the most long-term gains. The reward function penalizes the same sequential replies to integrate the incentive of knowledge flow. Using the negative log of the cosine relationship between successive encoder representations, the penalty is computed. The forward and backward frequencies of talk creation are scaled by their goal durations to determine their reward. A weighted total of these three incentives creates the last part of the reward function. After supervised learning systems begin to function at scale and engage with a broad user base, reinforcement learning is employed. RL which is based on policy gradients is used to optimize. In addition to calculating the reward, model weights are used to update the gradients of the action probability. Better answers in this strategy result in bigger incentives and a positive gradient, which raises the action's likelihood. DRL often relies on training deep neural networks to approximate the ideal value functions V*, Q*, and A* and/or the optimal policy π*.

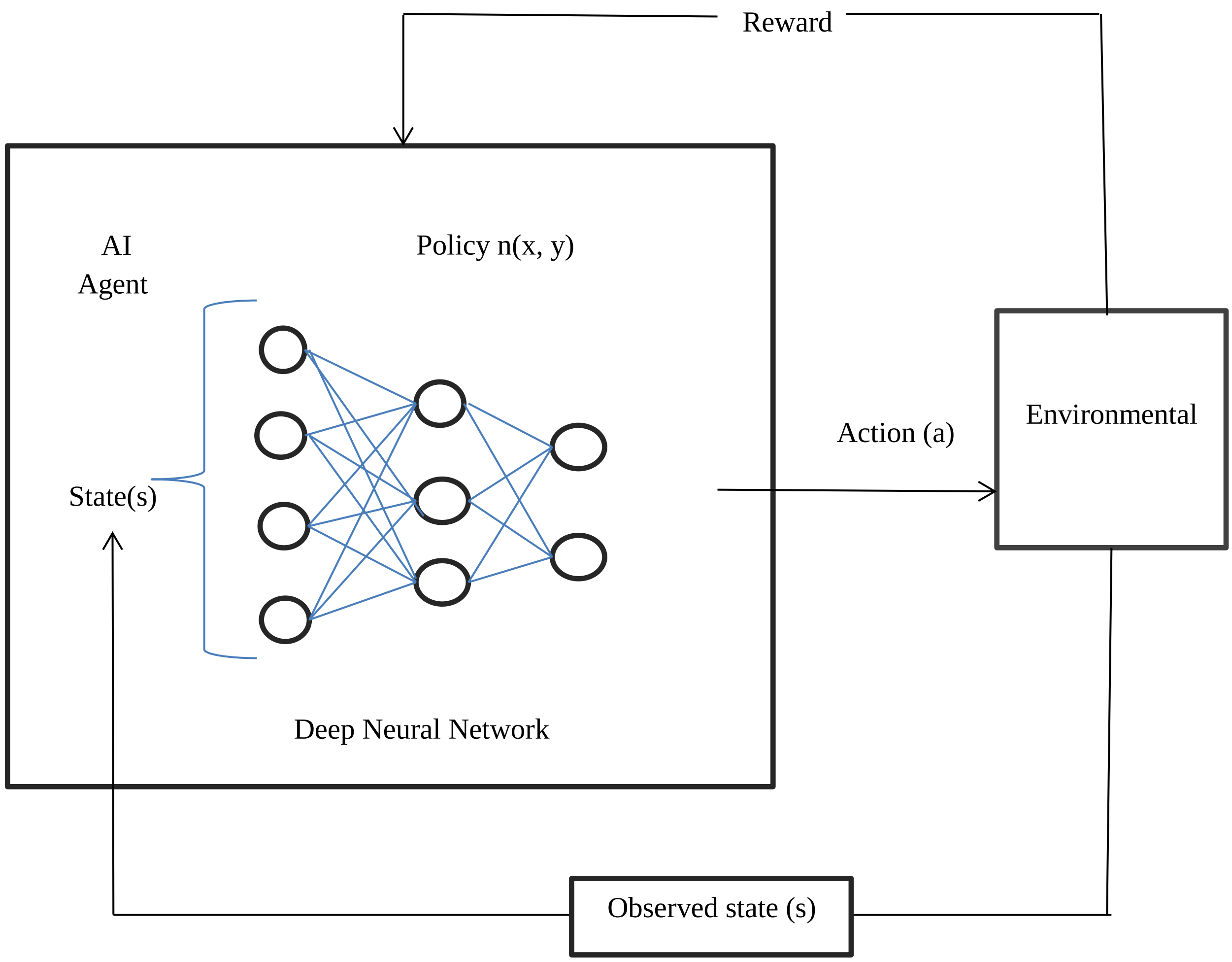


Figure 2. Deep Reinforcement Learning Architecture

**Artificial Intelligence Resource Management with Deep Reinforcement Learning**

Reinforcement learning is primarily used for addressing ordered multistep decision-making problems in which the system (RLS) must learn from its knowledge because the external environment provides minimal data. In these situations, the RLS learns in an action-evaluation environment and adapts the action plan to the present surroundings. Reinforcement learning is a significant area of machine learning study because of its postponed reward and trial-and-error search functions. Intelligent body learning must take a comprehensive approach, both short-term and long-term accumulation rewards [19]. Reinforcement learning continually changes the mapping method from the current situation to act in a learning way [20].

DRL, a subfield of machine learning that combines RL and DNN capabilities, has been widely used in recent years to address a variety of difficult problems in a variety of disciplines. To effectively extract characteristics, manage high-dimensional input fields, and simulate complex methods, DRL takes advantage of this invention. DRL is widely utilized to handle issues involving sequential selection creation, which may be stated mathematically as an MDP [21]. An MDP is a decision-making approach that finds the best actions to be done at each step of a time-varying stochastic model.

It is defined by a series of numbers (Y, X, u, v), where Y stands for a finite set of states, X for a limited set of measures, and u for the likelihood of changing from state to state′ after the action is carried out. R for the immediate reward after the action is carried out. A mapping from a state to an action is called $\boldsymbol{\alpha}$, or policy. Finding the best policy $\boldsymbol{\alpha}*$ that maximizes the reward function provided by u∞ t=0 γ rt(mt, nt), where nt = $\boldsymbol{\alpha}*$(mt) and γ ∈ [0, 1], is the main objective of an MDP.

DRL is becoming a more effective technique for Artificial intelligence resource allocation strategy optimization. DRL may be used to overcome the difficulties in rapidly changing and complicated wireless networks, where effective Artificial intelligence resource allocation takes precedence. Models can continuously modify power distribution, bandwidth consumption, and planning regulations to enhance network performance by utilizing DRL's adaptive learning capabilities [22]. When traditional approaches struggle to adjust to situations, this is quite beneficial.

In reinforcement learning, the Q-learning technique is a model-free method determining the best course of action for a finite MDP. Iteratively, the Q-value for a state-action pair is updated. According to the equation:

$$\mathrm{Q(mt, nt) \leftarrow (1 - n)\ Q(mt, nt) + n[rt + \delta\ maxaQ\ (mt + 1, n)]} \tag{1}$$

Where n is the learning rate and mt+1 represents the next state. The Q-learning approach has the benefit of dealing with reward delays and not requiring information on the environment's change frequencies. The loss functions reduce the variation between the goals and present Q-values so that the Q-network can converge to an estimate of the ideal action values [23]. Resource block splitting is handled as a DRL task to enable intelligent and adaptive decision-making that effectively allocates spectrum capacity and enhances overall network performance and effectiveness.

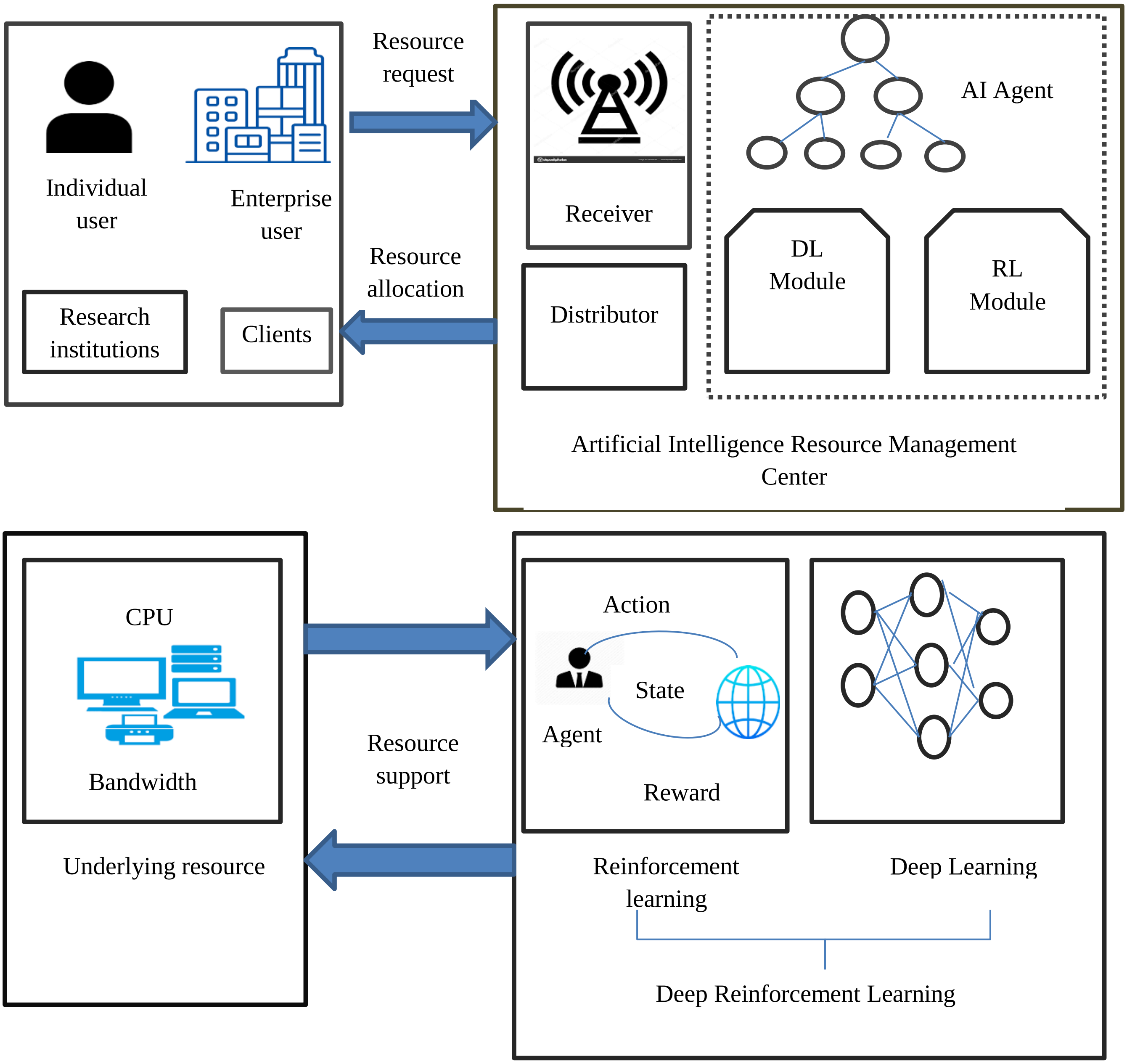


Figure 3. Proposed Artificial Intelligence Resource Management with Deep Reinforcement Learning

Figure 3 Shows the proposed Artificial Intelligence Resource Management with Deep Reinforcement Learning. The design of network end users can take many forms, provided that the users who must request network resources are regarded as end users. It mostly consists of research institutes, business users, and individual users. The network service center receives the request for virtual network resources from the network end user. The resource manager, which is housed in the Artificial Intelligence Management Center of Network Resources, uses the receiving port to receive requests from end users for network resources and the distribution port to distribute them to various end users. Deep learning and reinforcement learning work together to complete the scheduling of network resources. The best resource allocation plan is determined based on several objectives once the DRL agent has been trained in various network environments. VNE is the term used to describe the logical distribution of the underlying network resources for these virtual networks. The underlying resources, which mostly consist of CPU and bandwidth resources, are dispersed throughout the underlying resource pool.

In RL, the state space is the agent's field of play, where they may execute behaviors to change the state sequentially while trying to maximize their total reward. An extensive collection of data that gives the agent the context it needs to make wise judgments is included in the state space. The state space may be seen from two angles: the environment, which assesses the performance of the agent based on the quality of the design, and the agent's, where actions are done depending on the current state to achieve the design target (reward). Therefore, to make decisions, agents and the environment both need to know the state.

In RL, the reward function is essential for directing the agent's learning process. It offers a quantitative assessment of the agent's activities' quality or attractiveness and their environment [24]. By using the reward function as a feedback signal, the agent may assess the things of its choices and gradually learn to maximize cumulative rewards. In RL, the collection of possible actions an agent might do in a particular state is represented by the action space. The agent's is to identify a series of actions that will move it from the starting point to the desired state.

**QoS Mapping**

Quality of service (QoS) refers to the network-based technologies or procedures to manage traffic and guarantee the operation of vital applications with constrained network resources. It allows businesses to prioritize particular high-performance apps and modify their whole network traffic. Real-time QoS monitoring techniques are incorporated into the suggested optimization framework to track and assess the three main QoS parameters—bandwidth, latency, and packet loss—essential for VR applications [25].

The gathered QoS metrics are used as data to calculate mean opinion score (MOS) values, a measure that provides a user-centered evaluation of the quality of video streaming. A correlation model must be created to determine the relationship between QoS parameters and their respective and combined effects on QoE [26]. IQX hypothesis is an exponential technique that uses a generalized unfavorable exponential equation of a QoS impairment characteristic to represent QoE.

$$\mathrm{QoE} = \alpha(\mathrm{I1}, \mathrm{I2}, \dots \dots \dots \dots \dots \dots \dots \mathrm{In}) \quad (2)$$

Where QoE- Quality of experience, $\boldsymbol{\alpha}$- learning rate. QoS can be expressed as a function of n, influence factors Ij, $1 \leq j \leq n$:

The IQX theory establishes the underlying association QoE = f (QoS) by concentrating on a single influencing component, I = QoS. When QoE levels are high, subjective reactivity to changes in QoE is usually most noticeable. This situation occurs because when QoE is excessively high, even a slight drop in quality is immediately noticed. On the other hand, the subsequent decline is less noticeable when QoE is already low. To a linear connection at the QoE level, the differential equation below is modified.

$$\frac{\delta \mathrm{QoE}}{\delta \mathrm{QoS}} = \Upsilon - (\mathrm{QoE} - \Upsilon) \quad (3)$$

Where $\gamma \in [0, 1]$ denotes the discount factor.

The IQX hypothesis's basic link is captured by the exponential function that results from this equation.

$$\mathrm{QoE} = \alpha e^{-\beta \mathrm{QoS}} + \gamma. \quad (4)$$

Where α, β, and γ coefficients are adjustable parameters.

**Deep Learning Functional working**

Resources Management in networks may be used more efficiently thanks to machine learning-based Artificial Neural Networks, which are becoming increasingly important resource management algorithms that address the issue of distributing resources across various infrastructure nodes. Algorithms for resource allocation based on machine learning (ML) calculate the best way to distribute resources within a system using economic and computational approaches. These methods seek to optimize the network's overall efficiency while staying below the constraints of the resources at hand [27]. The algorithms show the limitations of the resources at their disposal and attempt to reduce a variety of goals, including latency, outage, cost, and power usage. Figure 4 displays a functional diagram for deep learning.

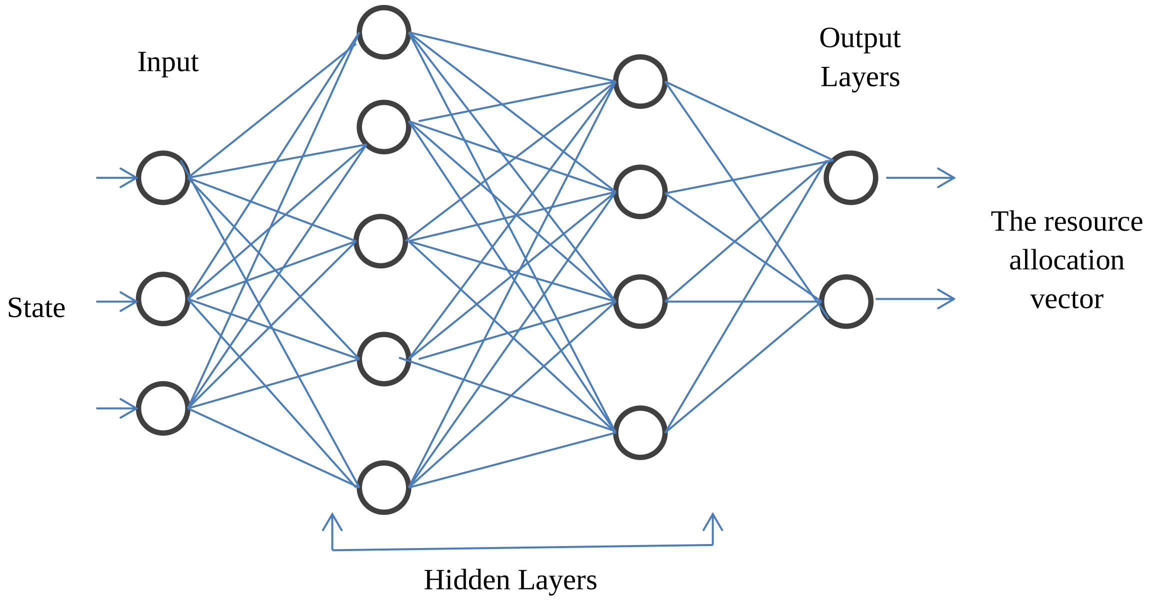


Figure 4. Deep Learning Functional diagram

Subsequently, the algorithm must determine the optimal strategy to ensure the node maximizes its resources. The techniques will monitor the environment after allocation to ensure that each node has the capacity it requires and to allow the network to adjust as new nodes join. Additionally, this guarantees that the network can precisely and swiftly adapt to shifting environmental circumstances.

## 4. EXPERIMENTAL RESULTS AND ANALYSIS

Performance analysis of resource management techniques based on Artificial intelligence with machine learning is a term that refers to the assessment of technology-based algorithms' efficiency within networks. The proposed method DRL based on Artificial intelligence in resource management is calculated, utilizing the MATLAB platform to simulate the suggested architecture. Between 200 and 1000 nodes might be used in this experiment. These nodes are dispersed across an area of 1000 x 1000 m². Artificial intelligence with Machine learning-based resource allocation approaches are widely used to identify optimal frequency ranges, beam shaping factors, and radio access networks. These algorithms determine the optimum uses of frequency and other resources to meet the network's goals and requirements. The numerical results show that it performs competitively in terms of bandwidth of 97.5%, power consumption of 96%, spectrum efficiency of 91%, and network lifespan of 93 percent. The proposed model RM_WN_DRL has been compared with the existing WL-DCNN, RNN, and WSN-IoT. WSN-based resource management employing deep reinforcement learning for energy efficiency with data optimization is compared in the tables below.

Table 1. Analysis of Bandwidth

| No. of Nodes | WL_DCNN | RNN | WSN_ IoT | RM_WN_DRL |
|---|---|---|---|---|
| 200 | 66 | 67 | 70 | 74 |
| 400 | 70 | 72 | 75 | 78 |
| 600 | 72 | 75 | 77 | 85 |
| 800 | 75 | 78 | 80 | 91 |
| 1000 | 77 | 80 | 85 | 97.5 |

Table 1 displays a comparison of several bandwidth methods. Between 200 and 1000 nodes might be used in this experiment. These nodes are dispersed across an area of 1000 x 1000 m². The numerical results show that it performs competitively in terms of bandwidth of 97.5%.

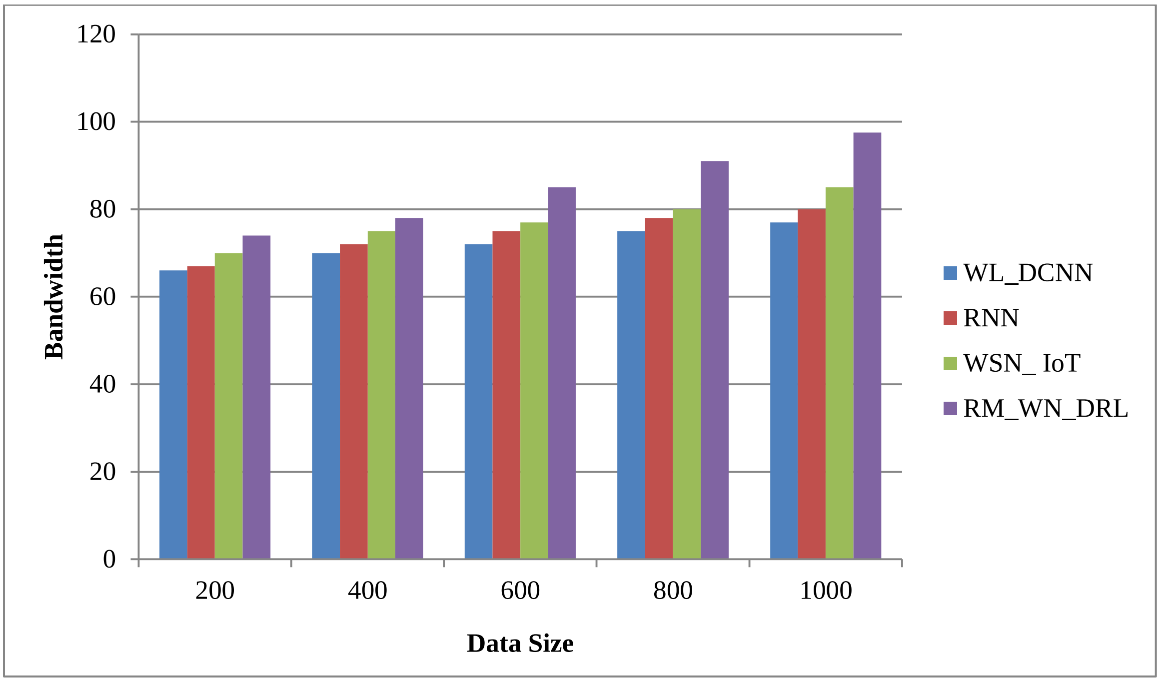


Figure 5. Analysis of bandwidth

Figure 5 presents a comparative study of deep learning-based WSN-based resource distribution in energy efficiency with data optimization. Commonly used algorithms include WL_DCNN, RNN (recurrent neural network), WSN-IoT, and RM_WN_DRL. Compared with WSN-IoT, the RM_WN_DRL Bandwidth is more efficient.

Table 2. Analysis of Power Consumption

| No. of nodes | WL_DCNN | RNN | WSN_ IoT | RM_WN_DRL |
|---|---|---|---|---|
| 200 | 72 | 74 | 76 | 80 |
| 400 | 74 | 76 | 80 | 83 |
| 600 | 77 | 78 | 84 | 87 |
| 800 | 80 | 81 | 87 | 94 |
| 1000 | 84 | 85 | 89 | 96 |

The comparison of several algorithms for power consumption is shown in Table 2. Between 200 and 1000 nodes might be used in this experiment. These nodes are spread out over a 1000 x 1000 m² region. The numerical results show that it performs competitively in terms of power consumption of 96%.

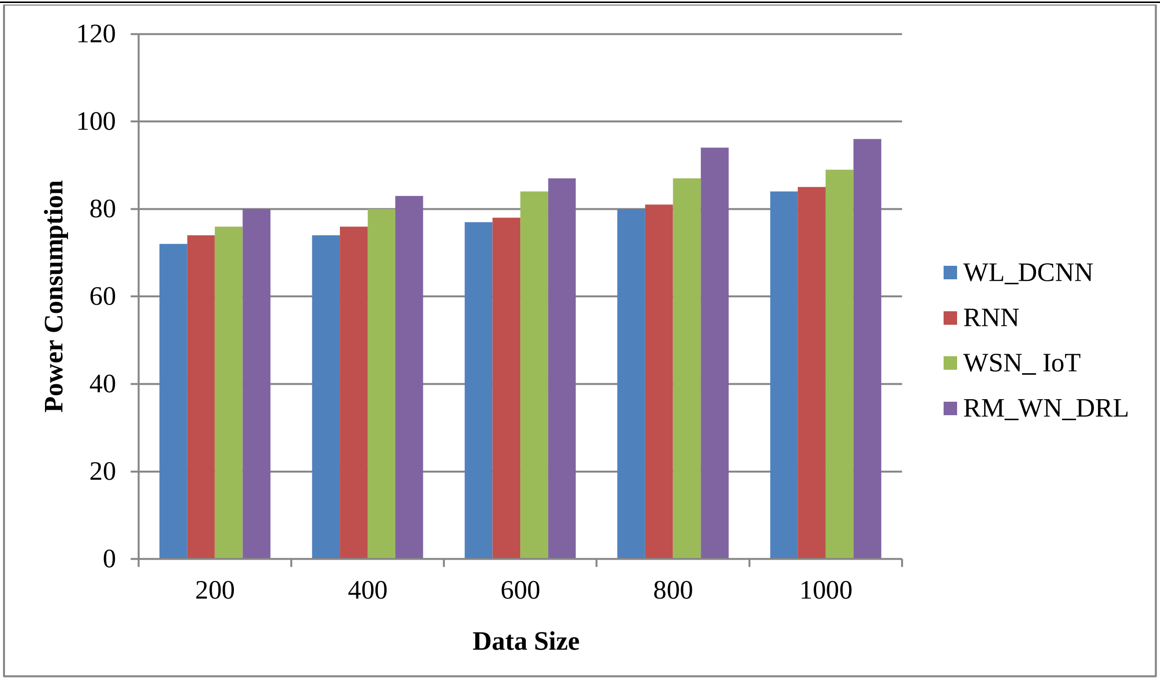


Figure 6. Analysis of Power Consumption

A Comparative analysis of deep learning-based WSN-based resource allocation in energy efficiency with data optimization is presented in Figure 6. Commonly used algorithms include WL_DCNN, RNN (recurrent neural network), WSN-IoT, and RM_WN_DRL. Compared with WSN-IoT, the RM_WN_DRL Power Consumption is more efficient.

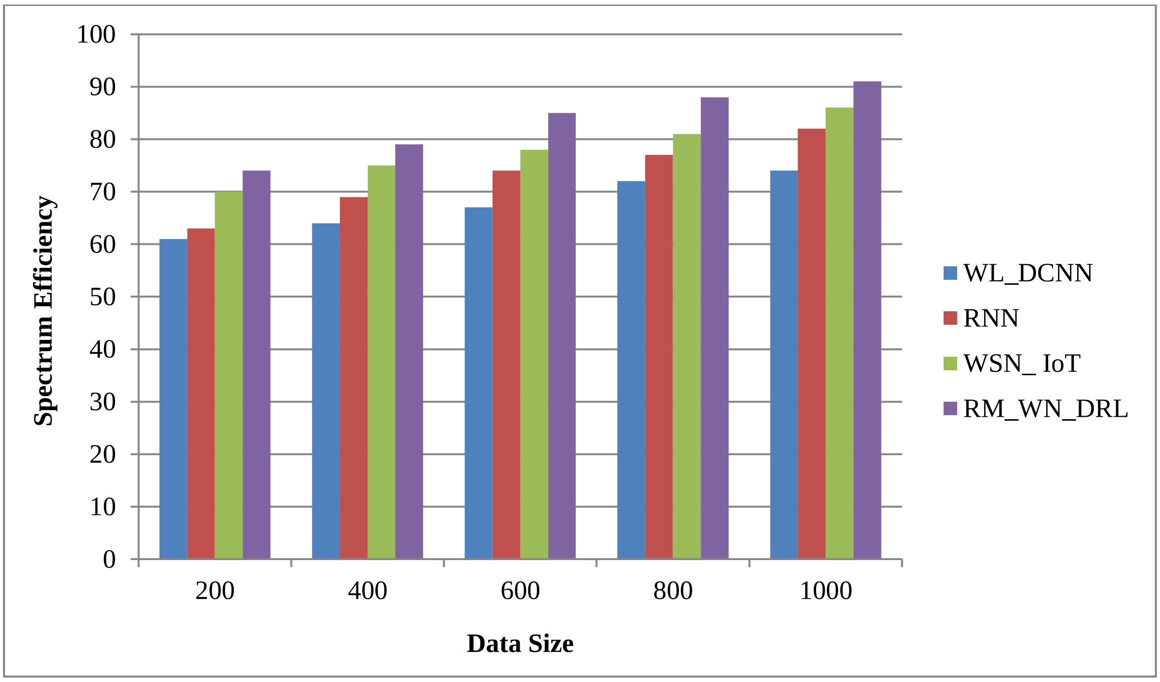


Figure 7. Analysis of Spectrum Efficiency

To evaluate machine learning-based resource allocation algorithms, several resource allocation techniques are examined and contrasted, as seen in Figure 7. The benefits and drawbacks of each technique to determine which is best. Commonly used algorithms include WL_DCNN, RNN (recurrent neural network), WSN-IoT, and RM_WN_DRL. Compared with WSN-IoT, the RM_WN_DRL Spectrum Efficiency is more efficient.

Table 3. Analysis of Spectrum Efficiency

| No. of nodes | WL_DCNN | RNN | WSN_ IoT | RM_WN_DRL |
|---|---|---|---|---|
| 200 | 61 | 63 | 70 | 74 |
| 400 | 64 | 69 | 75 | 79 |
| 600 | 67 | 74 | 78 | 85 |
| 800 | 72 | 77 | 81 | 88 |
| 1000 | 74 | 82 | 86 | 91 |

A comparison of several Spectrum Efficiency techniques is shown in Table 3. There might be anything from 200 to 1000 nodes used in this experiment. These nodes are dispersed across an area of 1000 x 1000 m². The numerical results show that it performs competitively in positions of spectrum efficiency of 91%.

Table 4. Analysis of Network Lifetime

| No. of nodes | WL_DCNN | RNN | WSN_ IoT | RM_WN_DRL |
|---|---|---|---|---|
| 200 | 63 | 66 | 70 | 72 |
| 400 | 66 | 69 | 76 | 78 |
| 600 | 68 | 74 | 80 | 84 |
| 800 | 69 | 77 | 87 | 89 |
| 1000 | 74 | 81 | 90 | 93 |

The main comparison variables are latency, complexity, and frequency spectrum efficiency. Table 4 shows the comparison of several algorithms for network longevity. Commonly used algorithms include WL_DCNN, RNN (recurrent neural network), WSN-IoT, and RM_WN_DRL. Compared with WSN-IoT, the RM_WN_DRL Network Lifetime is more efficient. While difficulty indicates the work required for implementation and maintenance, frequency effectiveness of spectrum quantifies the overall amount of spectrum used over a certain period. The amount of time it takes for the algorithm to react to environmental changes is known as latency. In a given situation, one approach could work better than another based on the individual circumstances. Therefore, this kind of comparison can assist in determining which resource allocation technique is best suited for a certain system.

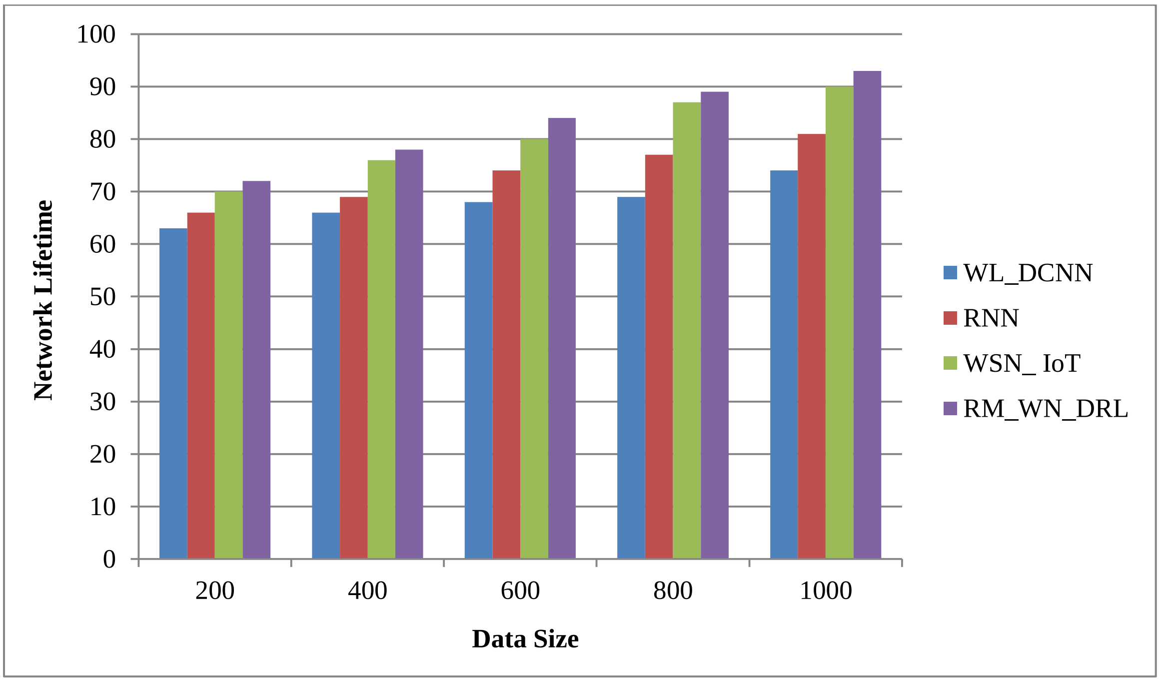


Figure 8. Analysis of Network Lifetime

Analysis of Network Lifetime is shown in Figure 8. The above presents a comparative study of deep learning-based WSN-based resource distribution in energy efficiency with data optimization. Bandwidth, Power consumption, and spectrum efficiency are all included in this parametric study. The numerical results show that it performs competitively in terms of bandwidth of 97.5%, power consumption of 96%, spectrum efficiency of 91%, and network lifespan of 93%. Based on the study, the suggested approach has optimized data and energy efficiency.

## 5. CONCLUSION

In this proposed work, deep reinforcement learning (DRL) based on machine learning is an essential tool for addressing the issues of resource management. Artificial Intelligence Resource management has to be dynamic since the actual server's load varies over time. Dynamic resource management is quite challenging, mostly when QoS must fluctuate constantly while taking processor availability and idle time into account. Future studies must concentrate on strengthening the DRL model's flexibility and robustness in situations of extreme congestion. High efficiency is demonstrated by the DRL-based Artificial intelligence resource management models specifically created to maximize the QoS variables in selected UEs. Effective resource distribution is a key component of resources under spectrum availability restrictions. Because DRL is adaptive, the resource allocation model can respond instantly to changes in network conditions. This research might increase bandwidth, power consumption, spectrum efficiency, and resource management, with a particular emphasis on automation, efficiency, and prediction via quality of service. In this paper, the numerical results show that it performs competitively in terms of bandwidth of 97.5%, power consumption of 96%, spectrum efficiency of 91%, and network lifespan of 93 percent.

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