# Energy-Efficient Internet of Things-Based Wireless Sensor Networks through AI-Powered Resource Allocation

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Abstract: Adaptable, energy-efficient, and data-optimized environments are now achievable through the integration of wireless sensor networks (WSNs) and the Internet of Things (IoT). However, challenges such as resource constraints, high energy consumption, and inefficient communication protocols limit their effectiveness. To address these issues, this study employs the Whale Optimization Algorithm (WOA) in an AI-based approach. The proposed method optimizes resource allocation by minimizing communication costs, balancing network loads, and enhancing energy efficiency. Experimental results demonstrate significant improvements in network lifetime, throughput, and spectral efficiency. These findings highlight the effectiveness of AI-driven techniques in significantly boosting IoT network reliability, longevity, and resilience against operational challenges. By leveraging intelligent optimization, the proposed solution not only enhances WSN performance in IoT applications but also streamlines resource allocation and energy efficiency. This makes it a promising approach for next-generation smart homes, industrial IoT environments, healthcare monitoring, and other IoT-driven systems. The study underscores the substantial potential of AI-based optimization in overcoming key limitations of WSNs, paving the way for more sustainable, scalable, and efficient IoT deployments across diverse applications.

## 1 INTRODUCTION

With the convergence of the IoT, smart environments have become more connected, adaptive, proactive, and intelligent. Most adaptive environments are not designed with human emotions and preferences in mind, despite the fact that they are intended to facilitate people's daily lives [1]. Today, technology is mainly accessed through the senses of sight and sound. According to predictions, a full internet of senses will be established by 2025, including taste, smell, and sight. Also, by 2030, it may be possible to communicate thoughts digitally, which eliminates the need for mice and keyboards as a user interface [2]. Through the Internet of Senses, emotions and preferences will be transparently integrated without requiring direct feedback from users, resulting in a more personalized experience.

The Wireless Sensor Network (WSN) uses multiple sensors to monitor environmental parameters, including temperature, humidity, and moisture. There are a variety of sensors on the device, including electroacoustic sensors, pressure sensors, motion sensors, image sensors, chemical sensors, weather sensors, pressure sensors, temperature sensors, and optical sensors. A wide range of applications can benefit from WSNs, including healthcare, military, defence, agriculture, and our everyday lives [3]. While WSNs have a wide range of applications, they face many challenges, including limited energy resources, computing speed, memory, and communication bandwidth, which result in a decrease in performance over time [4]. A variety of algorithms can be developed for different applications, which can be quite challenging. As part of the design of a WSN, designers should consider a number of factors, including data aggregation, clustering, routing, localization, fault detection, task scheduling, and event tracking, among others.

WSNs are multi-hop wireless networks that allow things to communicate in a monitored area, and the IoT depends heavily on them [5]. WSNs play a key role in IoT applications by enabling nodes to cooperate to provide high-functioning IoT applications [6]. IoT applications have high Quality-of-Service requirements, so deploying energy-efficient nodes and adjusting resources in collaboration is critical in WSNs. As shown in [7], next-generation wireless networks incorporating artificial intelligence technology can improve machine learning. As a result of artificial intelligence's distributed capabilities, the wireless communication system as a whole has been surprised [8].

It has been proven that emotion-aware applications improve user experiences and system efficiency in wireless networks. In addition to cognitive radio ad-hoc networks [9], mobile cloud computing is also an example [4]. With the increasing use of emotional-aware applications, such as network personalization, services are being tailored to meet the needs and prospects of operators in continually changing environments.

Resource management is considered a key task for ensuring network connectivity because sensor nodes have inhibited power supplies. Additionally, in general, network operations consume a greater amount of energy due to communication between members. The efficient use of power can reduce the rapid exhaustion of energy in sensor nodes, improving their performance as a result. Energy efficiency, therefore, deserves a lot of attention. Many factors challenge the sensor network's functionality, such as power restrictions, insufficient processing power, etc. Sensor nodes in the network continuously gather data, which causes the battery to deplete extremely quickly. An effective strategy for managing data transmission and energy-efficient communication can significantly extend the lifetime of a network [10].

Clusters of sensor nodes are arranged hierarchically according to their type. There will be a distinction between nodes within a cluster according to their functionalities. Two-layer WSN architectures delegate nodes to collect and relay data from the surroundings to their respective heads. It is these heads that aggregate the inferred data and transmit it [11]. It is more important to schedule cluster update cycles at the appropriate time and place and to nominate sensor members to operate as the head nodes at the appropriate time. Without appropriate selection, the member nodes will experience premature energy shortfalls. In terms of the limitations of the available approaches, the cost of repeated message transmissions and the difficulty in exchanging messages through the formation of clusters are the key limitations.

# 2 LITERATURE REVIEW

The nearest neighbour algorithm and dynamic programming are common resource allocation algorithms in WSNs. According to the paper [12], resources should be allocated centrally. A high quality of service reduces energy consumption and enhances the utilization of broadband when it constrains resources. Using integer linear programming (ILP), a method for assigning tasks to wireless sensor networks (WSNs) in static environments is presented [13], and the nodes' overhead in communication and computation is accounted for in this calculation. In the works, the allocation of resources in the network is also based on the ILP method, but the primary consideration is the quality of the information [14]. In spite of this, the network requires efficient and dynamic resource allocation mechanisms to meet users' increasing demands. A market-based resource allocation method is used by [15] to optimize the utilization of sensor resources in competition.

A dynamic resource scheduling system has also been developed by the author [16] by applying game theory. Nodes in WSNs are assigned roles based on queuing rather than randomly. Typical WSN scenarios involve steady-state analysis to determine the optimal allocation scheme. The network remains energy-efficient and has a long lifespan when compared to other methods [17]. As part of the resource allocation process, all these methods assess the amount of energy consumed by the network. However, there is a need for different levels of quality of service for multiple publishing tasks. It is achieved by applying this concept to assign tasks to the corresponding nodes according to various quality of service requirements, thereby reducing resource utilization and improving resource efficiency.

A heterogeneous network presents a huge challenge for resource allocation due to its heterogeneous nodes. Heterogeneous WSNs can be allocated resources according to quality of service [18]. As a result of resource allocation constraints, maximizing network throughput is transformed into maximizing statistical quality of service [18]. An equitable network throughput and resource distribution scheme is proposed in the document. An optimal resource allocation scheme is presented in [19], which reduces interference and increases network throughput and speed. WSNs with heterogeneous topologies can benefit from layering protocols [20]. Author [7] illustrates how layering can effectively eliminate energy holes from networks. According to [21], the layered method can be improved by implementing an agent that updates the network state.

Additionally, the functionality of active head nodes is interchanged in order to stabilize the entire energy usage and adapt to topological changes in the network. Researchers studied Wireless Sensor Networks to balance energy consumption using these approaches. Because the head nodes are primarily responsible for gathering, managing, and forwarding data, they consume a lot of energy. A TDMA schedule is also assigned to each node, irrespective of whether the node has sensed readings to send. With Cell LEACH, clusters are further partitioned into different cells. During the lifetime of the network, clusters and cells will persist in addition to those created during the setup phase. There will be a dynamic reorganization of clusters [22].

A regular feature of sensor networks is the adaptation of Machine Learning (ML) strategies to minimize the need for redesign [23]. By optimizing resource management and extending the lifespan of networks, machine learning can enhance both. In recent years, ML has focused more on algorithms that can be computationally feasible. In different applications, these techniques can be used for regression, classification, etc. A sensor network observes dynamic situations that rapidly change over time. Smart policies can be made with the help of the IoT, according to a recent application [24].

Wireless sensor networks can benefit greatly from machine learning. For intuitive learning, decision-making, and identifying complex models, classification and data learning are the most appropriate and widely used techniques. Graph embedding is another technique for teaching graphs, which preserves their topological properties by learning graph representations. However, the initial data is not guaranteed to be intact with these dimensionality-reduction techniques [25]. In this article [26], the author uses convolutional neural networks to obtain node features in graph structure data and to create atomic fingerprints based on the features obtained. With the original graph link sets as inputs, a full connection neural network (FCNN) [27] was trained with the WLNM, a method proposed by the author [27] to build a link prediction model using the original graph link sets. A previously unstudied task, predicting link reliability, is addressed in this paper by applying the WLNM. Deep learning algorithms were used to design, implement, and evaluate a link-reliability-based routing algorithm for wireless sensor networks.

Link reliability is predicted by WL-DCNN combining Weissfeiler-Lehman sub-graph labelling with 2-branch convolutional neural networks. Moreover, the loss function was modified to account for imbalances in training samples and improve training set formation. Six public datasets demonstrate an efficient method for extracting topological features from complex networks, with up to 40% better predictions than baseline algorithms. WL-DCNN-based resilient routing algorithms ensure data integrity in sensor networks while reducing transmission paths and ensuring data integrity in vulnerable wireless links, as shown with our algorithm [28]. In addition to enhancing network durability and routing robustness, the nodes' power consumption is reduced as a result.

# 3 METHODOLOGY

The administration of IoT relies heavily on low latency and low energy consumption. As a first step towards achieving these goals, this paper focuses on the RA problem in IoT. A major goal of RA is to reduce communication costs and balance load. Network latency is reduced when communication costs are reduced. As a result of load balancing, network bottlenecks would be eliminated, and performance would be increased. Upon meeting these goals, this technology will be useful in many situations. This paper presents an algorithm based on particles.

Solving complex optimization problems has traditionally been done by heuristic algorithms. It is possible to devise a heuristic algorithm to find a solution to the RA problem because it is NP-complete. In this paper, we propose a new heuristic for solving the RA problem in cloud computing called WOA. Humpback whales are famous for their collective hunting technique, which inspired the whale algorithm. As a step toward solving the RA problem, we will examine WOA in detail.

## 3.1 Flowchart for the Proposed Algorithm

First, the 'whale-create' function is used to create whales. Scheduling problems are solved randomly by whales. Fitness analyses indicate that the BS is currently the optimal whale based on its fitness. RA patterns of whales are calculated based on the total communication cost. The following is an explanation of this function, which is titled 'fitness'. Whales begin moving after this step. A new $x$ , $X$ , $Y$ , $j$ , $F$ value is calculated for each whale. In this Equation, $X$ and $Y$ are constants. Numbers are descending from $x \in$

[2.0]. There are two random numbers, $F \in [2.0]$ and $j \in [2.0]$. In the following sections, we explain how these numbers are used.

Distance functions play an important role in whale algorithms. Due to the fact that whale algorithms were designed for continuous problems, RA is discrete. Based on the algorithm, this function calculates distance. There are three functions involved in controlling whale motion. We will start by reducing the distance between the best whale and the current whale using the shrinking function. In addition, there's a "spiral" function, in which the whales rotate around the best whale. Furthermore, whales are known to approach random whales as part of their "search prey" behaviour.

## 3.2 Whale Creating

In this algorithm, whales represent solutions to RA. A node is a gateway or a resource in the described problem. There are many gateways, and each gateway receives information from a certain number of resources. The cloud's complete flow of information is created by connecting gateways based on a certain topology. Due to data transmission costs, gateways are connected by spanning trees or rings with the fewest edges. It creates two sets of communications for each whale: a set of edges representing the connections between gateways and a set of edges indicating the resources that are allocated to each gateway. It consists of an array w with a size $k + n$, where $k$ is the number of gateways and $n$ is the number of resources. As shown in array $w\ (w[1.k]), the$ first $k$ entries, gateways are related. In this case, $w[i] = j$ indicates that gateway $j\ (i\ ,j)$. receives information from gateway $w[i] = j$. In array $w\ (w[k + 1.n])$ The second n entries represent each resource's gateway. Resources $F - k$ and $q$ are connected through gateway $q$, as indicated by $w[F] = q$.

## 3.3 Distance Function

In this algorithm, the distance function is used to calculate how far two whales are from each other, which is an important function to note. Whale algorithms are discrete algorithms, while RA problems are continuous ones, so distance needs to be redefined. Whale algorithms work based on distances. Using the "shrinking" function, we will reduce the distance between the best whale and the current whale in the first step.

Each whale has $k + n$ edges, similar to the RA graph. A gateway has $k$ resources, and a resource has n gateways. Therefore, we find that zero is the minimum distance, while $k + n$ is the maximum distance.

## 3.4 Spiral Function

There is a random number p in the interval [0, 1] that determines the type of whale motion for each whale. Once this number exceeds half, whale motion is made by using spiral functions, meaning the best whale is spiralled around in a circle. A new definition of spiral is needed for the RA problem.

## 3.5 Shrinking Function

Every time the algorithm is run, p is generated at random. In the case of a number less than 0.5, it is recommended to consider another random number, A. A less than 1 indicates that the shrinking function should be used. A whale's current behaviour is due to this function, which urges it to seek out the best whale or prey. While spirals revolve around their prey, shrinking functions move directly and faster towards them. As a result, it would be helpful if the search prey function was executed more frequently prior to the algorithm's conclusion.

Whales and prey are separated by shrinking functions based on the position of the whales and their prey. Based on the distance calculation, a percentage of non-equal entries moves towards the best whale by 50%.

## 3.6 Search Prey Function

The generation of new solutions can help algorithms avoid getting stuck in local optimums. To accomplish this, we use the search prey function. This function should be performed more often at the beginning. As a result, more options will be available at the beginning of the exploitation phase and during optimization. Using the Search prey function, a whale is directed to a randomly chosen prey animal. The distance between whales determines the method of moving between them, as described below.

## 3.7 Whale Optimization Algorithm (WOA)

An algorithm based on the Humpback whales meta-heuristics is called the WOA [29]. A random population of whales is produced in this algorithm before optimization begins. This method involves whales finding (optimal) prey locations and encircling or using bubble nets to append them (optimize). Humpback whales improve their current locations by following this method [29]:

$$d = |X \odot Z^*(t) - Z(t)|, \quad (1)$$

$$Z(t = 1) = Z^*(t) - X \odot d. \quad (2)$$

This example uses $d$ to represent the distance between prey $(t)^*$ and whale $Z(t)\odot$, while $t$ opinions for the current iteration. In the following definition, $A$ and $C$ represent constant vectors.

$$X = 2x \odot r - x, \quad (3)$$

$$Y = 2r. \quad (4)$$

Each time $r$ is iterated, $Z$ is a random vector with indexes between [0,1], with each index corresponding to the random number between [0,1]

Both methods can be used for bubble-net analysis. There are two ways to shrink encompassing: decreasing (3) value of a and decreasing A's value. Humpback whales following their prey also use helix-shaped movements to update their position:

$$Z(t + 1) = d' \odot e^{bl} \odot \cos(2\pi l) + Z^*(t). \quad (5)$$

A whale's distance from its prey is defined by $Z' = |Z^*(t) - Z(t)|$, while $b$ describes the shape of the logarithmic spiral and $J$ a randomly generated value $\in [-1.1]$.

$$Z(t = 1) = \begin{cases} Z^*(t) - X \odot d & if\ F < 0.5 \\ D' \odot e^{bl} \odot \cos(2\pi l) + Z^*(t) & if\ F \geq 0.5 \end{cases}. \quad (6)$$

Does $F \in [0,1]$ represent a random value that determines a determining the location of whales, either using the shrinking encompassing method or the spiral approach?

A Humpback whale explores for prey randomly in its discovery phase. Whales are positioned randomly rather than with the best search agents.

$$d = |Y \odot Z_{rand} - Z(t)|, \quad (7)$$

$$Z(t = 1) = |Z_{rand} - X \odot d|. \quad (8)$$

How many positions are there in the current population where $Z_{rand}$ is it chosen randomly? In the first algorithm, the WOA's structure is depicted as a whole.

# 4 RESULTS AND DISCUSSION

The proposed deep learning routing protocol was evaluated using MATLAB simulations. In the experiment, 200 to 1000 nodes were distributed over an area of 1000 x 1000 m. GEEC, TTDFP, and EADCR have been compared to WODNN HMOFA, as well as five other existing algorithms. In this analysis, a variety of performance metrics are evaluated, including throughput, energy efficiency, Quality of Service (QoS), and spectral efficiency. Figure 1 demonstrates the superior performance of 98% throughput, Figure 2 shows the 97% energy efficiency, Figure 3 illustrates the 77% QoS, Figure 4 demonstrates the 87% spectral efficiency, and Figure 5 shows the 93% network lifetime using the proposed technique. Based on these results, the proposed method was able to achieve optimized energy efficiency and data handling, confirming its efficiency in optimizing

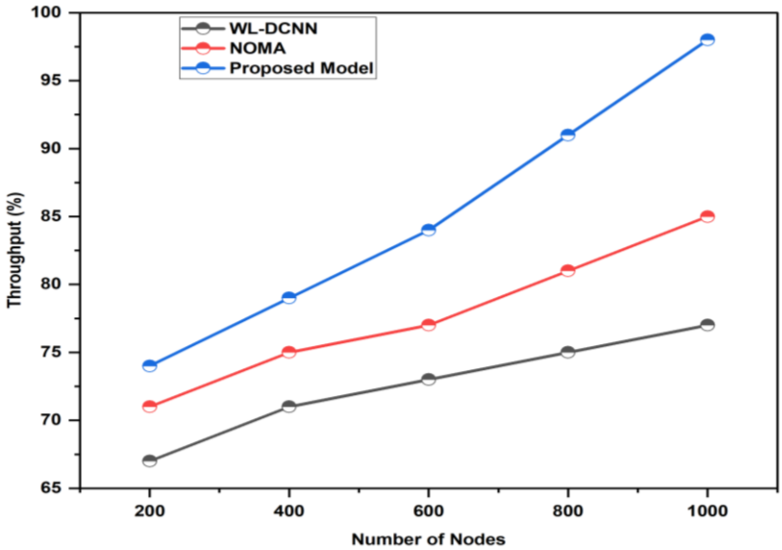


Figure 1: A comparison of throughputs versus number of nodes.

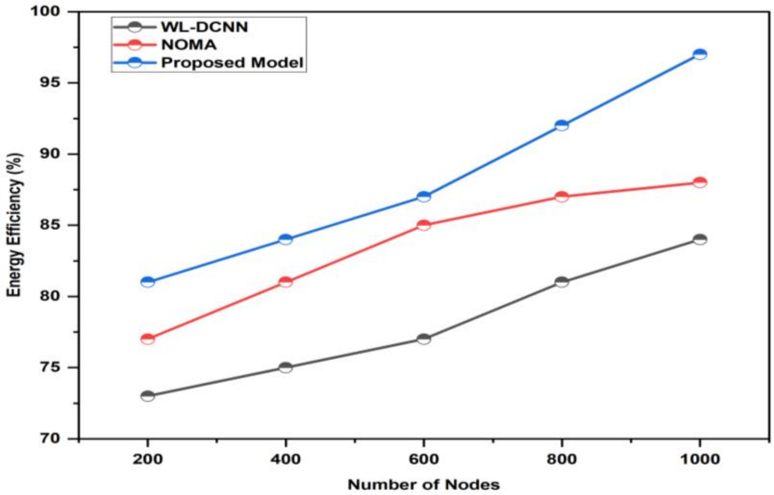


Figure 2: Energy Efficiency (%) versus number of nodes.

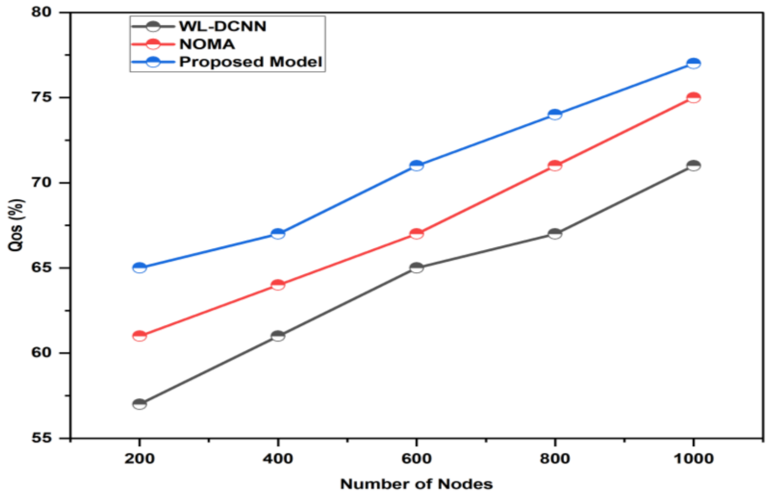


Figure 3: Quality of service versus number of nodes.

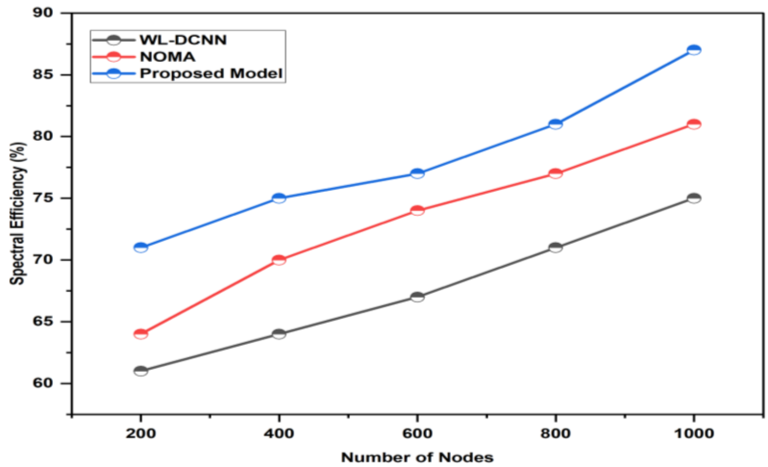


Figure 4: A comparison of spectral efficiency versus number of nodes.

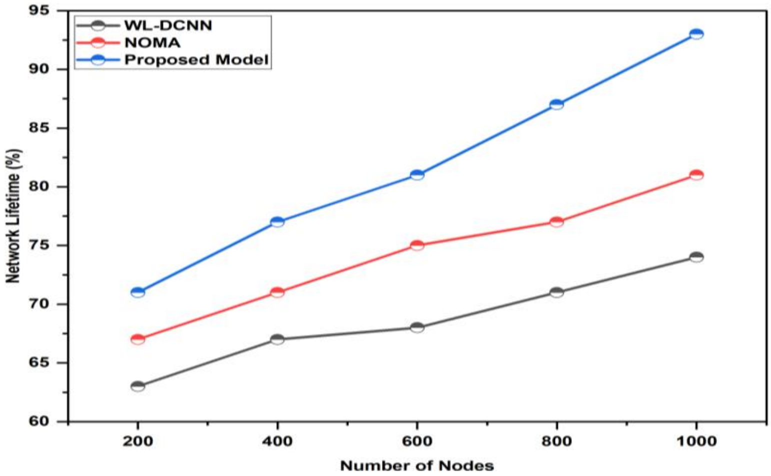


Figure 5: Analyzing the network lifetime versus number of nodes.

# 5 CONCLUSIONS

With the help of the Whale Optimization Algorithm (WOA), we have proposed an AI-driven approach to resource management in IoT-enabled WSNs that addresses critical challenges. A resource management strategy like this significantly improves energy efficiency, reduces communication latency, and enhances overall network performance and stability. According to detailed experimental evaluations and performance analyses, the proposed method demonstrates clear superiority in ensuring balanced load distribution across sensor nodes, maximizing energy utilization efficiency, and notably extending network lifetimes. These results highlight how IoT networks can substantially benefit from integrating advanced AI-based algorithms, thus enabling them to reliably meet the evolving demands of modern smart environments, including smart healthcare, agriculture, and industrial automation systems. Future research endeavors could further enhance the scalability, robustness, and performance of heterogeneous IoT networks by effectively integrating state-of-the-art deep-learning models with sophisticated optimization techniques, thus broadening potential applications and real-world effectiveness.

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