UDC 621.396
DOI: 10.15587/1729-4061.2024.310360

DEVELOPMENT OF METHODS FOR MONITORING AND OPTIMIZATION OF UNDERGROUND DRAINAGE SYSTEMS USING WIRELESS SENSOR NETWORKS AND ULTRA-WIDEBAND ANTENNAS

Kabi Yelikbay
Doctoral Student*
Pramod Kumar
Associate Professor, AIML (ECE)
Department of Electronics and Communication Engineering
CMR Engineering College
Medchal Rd, Kandlakoya, Seethariguda, Telangana, India, 501401
Ruslan Kassym
Corresponding author
Supervisor Project, Researcher**
University of Jaén
Campus Las Lagunillas s/n, Jaén, Spain, 23071
E-mail: kasym.ruslan@gmail.com
Tansaule Serikov
Doctor PhD***
Maxat Orunbekov
Senior Lecturer*
Ayinuer Turdy
Senior Lecturer*
Marzhan Temirbekova
PhD, Associate Professor**
Arai Tolegenova
PhD, Associate Professor***
Akmaral Tlenshiyeva
Senior Lector*
Makbal Kassymova
Researcher***
*Department Information and Communication Technologies**
**ALT University
Shevchenko str., 97, Almaty, Republic of Kazakhstan, 050013
***Department of Information and Communication Technology
S. Seifullin Kazakh Agrotechnical Research University
Zhenis ave., 62, Astana, Republic of Kazakhstan, 010011

This research focuses on optimizing ultra-wideband (UWB) antennas, which are critical in modern communication systems due to their wide frequency range (3.1–10.6 GHz) and high data transmission capabilities. The study addresses the challenge of optimizing key antenna parameters – such as return loss, peak gain, and radiation efficiency – while also ensuring energy efficiency and network longevity. Traditional optimization methods, such as LEACH-C, often fail to balance these factors, leading to suboptimal performance.

To solve this problem, the researchers developed the Generalized Position-based Optimization Neural Network (GPON) for UWB antenna optimization. They also evaluated the Position-based Hybrid Neural Network (PAN) method, comparing its performance with existing algorithms including LEACH-C, Firefly Algorithm (FA), HFAPSO, FA-ANN, and HWOABCA. The GPON model reduced return loss to 25.5 dB at 3.5 GHz and improved peak gain to 4.2 dB i, while maintaining 92 % radiation efficiency. In contrast, PAN demonstrated a 15–25 % improvement in residual energy and extended network lifetime by 20 % compared to LEACH-C.

These improvements were due to the integration of advanced neural network techniques in GPON and the effective use of positional data in PAN, enabling more precise and adaptive optimization. The ability to balance multiple performance metrics simultaneously – a challenge previous models struggled with – is a key feature. This balance is crucial for UWB antennas in communication systems where both performance and energy efficiency are vital. The findings are especially relevant for practical applications in wireless sensor networks, mobile communications, and radar systems, requiring long-term network reliability and optimal antenna performance

Keywords: ultra-wideband, antenna optimization, GPON, energy efficiency, network longevity, neural networks

Received date 19.07.2024
Accepted date 26.09.2024
Published date 30.10.2024

***How to Cite:** Yelikbay, K., Kumar, P., Kassym, R., Serikov, T., Orunbekov, M., Turdy, A., Temirbekova, M., Tolegenova, A., Tlenshieva, A., Kassymova, M. (2024). Development of methods for monitoring and optimization of underground drainage systems using wireless sensor networks and ultra-wideband antennas. Eastern-European Journal of Enterprise Technologies, 5 (5 (131)), 26–36. https://doi.org/10.15587/1729-4061.2024.310360*

1. Introduction

The topic of underground drainage systems is highly relevant in today's urban environments due to the critical role these systems play in maintaining public health, safety, and the overall functionality of cities. Inefficiencies or failures in drainage systems can lead to severe consequences, including flooding, sewage contamination, and the spread of harmful gases. Such issues can significantly disrupt daily life, particularly during rainy seasons, and may lead to serious public health crises if not properly managed [1]. The importance of regular and effective monitoring of drainage systems cannot be overstated, as it ensures the separation of clean water from sewage, thus preventing the spread of infections [2]. Traditional manual monitoring methods, however, are increasingly inadequate due to human physical limitations and the growing complexity of urban infrastructure. As a result, there is a pressing need to adopt technological advancements that can enhance the monitoring, sensing, recording, and analysis of both normal and abnormal conditions in these systems [3].

Wireless Sensor Networks (WSNs) have garnered significant attention in this context due to their wide-ranging applications across industries such as transportation, healthcare, and military operations. These networks, composed of sensor nodes that extend and integrate with larger networks, offer a promising solution for the real-time monitoring of underground drainage systems [4–6]. The use of WSNs in such applications is particularly advantageous due to their ability to operate in challenging underground environments and their potential for integration with other technologies, such as Ultra-Wideband (UWB) communication systems, which are essential for efficient data transmission and sensor localization [7]. Moreover, the communication industry's demand for higher quality, speed, and data rate transmission has further fueled interest in the development of advanced systems capable of overcoming the limitations of existing technologies [8]. UWB technologies, known for their wide bandwidth and ability to operate at high frequencies, are especially promising for underground monitoring applications, offering improved return loss, gain, and radiation efficiency when integrated with optimized antenna designs [9].

In this way, the Wireless Sensor Network has excellent benefits of monitoring the drainage systems composed of node sensors that extend and integrate with networks. The system interfaces with a PIC Microcontroller and employs various sensors such as a temperature sensor, a water level sensor, or a gas sensor to make the system as smart as possible. Wireless communication in underground environments is a significant challenge in realizing UWSNs. Regarding this, the UWB antenna is used to monitor the location of the sensor. Also, the antenna's parameter such as return loss, gain, and radiation is optimized using the proposed approach. The Hybrid Position-based Optimization Neural Network (HPONN) is used to improve return loss, peak gain, and radiation efficiency. Based on the process, the effectiveness of an antenna is also determined, and therefore, to compute the highest values of residual energy, it is compared with various optimization approaches.

Therefore, research on the development of advanced underground drainage monitoring systems, particularly those integrating Wireless Sensor Networks (WSNs) and Ultra-Wideband (UWB) technologies, is highly relevant. These innovations hold the potential to address the pressing challenges of urban infrastructure, improve public health and safety, and ensure the resilience of drainage systems in increasingly complex environments.

2. Literature review and problem statement

In [10], a sector-based integrated antenna was designed to improve network performance in wireless networks by expanding transmission range and increasing bandwidth. Although the study demonstrated a reduction in communication overhead by using random and serialized methods to detect neighbors, it suffered from low accuracy, indicating the challenge of balancing efficiency with precision in such systems. Similarly, [11] presented wireless systems for underground environments such as mines and tunnels, focusing on stable electromagnetic wave propagation in high-voltage conditions. While stable results were achieved using a modified multimode channel model, the system's low efficiency in challenging environments highlights a significant problem in maintaining high performance under harsh conditions.

In [12], dynamic switching of communication modes was proposed depending on battery capacity and environmental conditions, which improved communication stability. However, this approach also faced challenges with low accuracy and efficiency, emphasizing the difficulty of optimizing wireless network configurations under varying constraints. The introduction of Internet of Underground Things (IoUT) in [13] aimed to address soil characteristic monitoring, particularly soil moisture. Despite this innovation, the challenge of low accuracy in permittivity assessment persists, posing a major limitation to achieving reliable sensing in agricultural applications.

A further study [14] developed an energy efficiency maximization algorithm (EEMA) supported by autonomous underwater vehicles (AUVs) to minimize energy consumption in underwater networks. Although it extended the system's service life, data redundancy and increased energy consumption became critical issues, reflecting the trade-offs between energy efficiency and data transmission reliability.

In [15], a ring antenna for ultra-wideband (UWB) applications was designed, achieving a return loss of 34.22 dB at a resonant frequency of 3.54 GHz. However, the antenna suffered from low gain and high recoil losses, emphasizing the need for better optimization techniques. This aligns with broader concerns over traditional metaheuristic optimization methods, which tend to incur high computational costs and slower convergence rates while being prone to local optima. The conical slit antenna array developed in [16] aimed to create a broadband underwater connection with high gain. While it achieved a bandwidth of 55 %, a maximum realized gain of 10.75 dB i, and radiation efficiency of 90 %, potential electromagnetic interference remains a critical issue, affecting the overall reliability of underwater communications.

A conventional circular flat monopole UWB antenna was proposed in [17] for a range of applications, including Wi-Fi and underwater communications. Despite achieving a wide impedance bandwidth (2.66–11 GHz) and high radiation efficiency (96.6 %), the miniaturization required for this antenna design led to reduced gain, signaling a significant challenge in balancing size and performance. In [18], an improved PSO (Particle Swarm Optimization) algorithm was introduced to optimize UWB antenna design using a neighborhood-redispatch method. While the algorithm improved work quality, it required numerous control measurements, creating an issue with efficiency in terms of optimization validation.

Finally, [19] investigated an orientation-dependent UWB transceiver, using deep learning to enhance range accuracy. Despite significant accuracy improvements, the requirement for complex deep learning algorithms in dynamic environments added another layer of complexity, making implementation less practical for many applications.

Across these studies, recurring problems include low accuracy, reduced efficiency, high computational costs, and challenges in balancing size, performance, and optimization. These issues remain unresolved, as traditional optimization methods struggle to meet the evolving demands of wireless communication systems, particularly in complex environments like underwater, underground, and high-energy scenarios. All this allows to assert that it is advisable to conduct a study on the development and optimization of a Hybrid Position-based Optimization Neural Network (HPONN) to improve antenna performance, with a specific focus on parameters such as return loss, peak gain, radiation efficiency, and residual energy, addressing the shortcomings identified in the aforementioned studies.

3. The aim and objectives of the study

The aim of the study is to develop and optimize a Hybrid Position-based Optimization Neural Network (HPONN) for improving the performance of antennas, specifically focusing on parameters such as return loss, peak gain, radiation efficiency, and residual energy.

To achieve this aim, the following objectives are accomplished:

– to propose a hybrid neural network (GPON) to optimize and obtain optimal characteristics of an ultra-wideband (UWB) antenna;

– to evaluate and compare the method of location-based hybrid neural network optimization (PAN) with other optimization algorithms.

4. Materials and methods

The main object of the research is the design, modeling and optimization of an ultra-wide-band antenna (UWB) for use in underwater wireless sensor networks (UWSNS). In particular, the aim of the study is to improve key performance indicators such as return loss, peak gain, and radiation efficiency by integrating a hybrid location-based optimization neural network (HPONN) that combines machine learning with hybrid optimization algorithms.

The hypothesis of the study is that the proposed hybrid location-based optimization neural network (HPONN), which combines the whale optimization algorithm (WOA) and the artificial bee colony algorithm (ABC), will surpass existing optimization methods (such as LEACH-C, the Firefly algorithm and the hybrid neural network of artificial bee whale optimization, Colony Algorithm) in optimizing the parameters of ultra-wideband antennas for UWSN applications. HPONN will improve antenna performance in terms of reverse loss, peak gain and radiation efficiency, making the antenna more reliable for underwater communications.

The conditions of the underwater environment (shallow and deep water) are accurately represented in MATLAB modeling, including signal attenuation and track losses. Performance data collected for artificial neural network (ANN) training reflects the behavior of the antenna in the real world in a given frequency range. The sensor nodes in the UWSN operate with constant signal quality and behave in accordance with simulation models of underwater acoustic channels. ANN integration with the location-based Hybrid Optimization Algorithm (PHOA) allows reliable prediction and optimization of antenna performance in various underwater conditions.

Simplifications adopted in the study:

– the MATLAB simulation environment simplifies complex underwater dynamics such as changes in currents, pressure, temperature, and salinity that can affect signal propagation;

– the study does not take into account potential equipment flaws or manufacturing tolerances that may affect the operation of the UWB antenna in real conditions;

– the model assumes idealized conditions for communication between underwater nodes and a surface receiving node, simplifying the actual environmental interference or noise factors that may affect signal transmission;

– optimization algorithms assume uniform placement of sensor nodes and do not take into account dynamic changes in the location of nodes due to undercurrents or other physical forces.

The development and optimization of the Ultra-Wide Band (UWB) antenna for Underwater Wireless Sensor Networks (UWSNs) were carried out using the MATLAB software environment, which provided the necessary tools for designing, simulating, and fine-tuning the antenna parameters. MATLAB played a pivotal role in enabling precise simulations and detailed analyses, as it facilitated the modeling of both the antenna structure and the optimization algorithms used for performance enhancement.

For the antenna design, a Conventional Circular Planar Monopole Ultra-Wide Band (CCPMUWB) antenna was selected. This antenna was designed to operate within the frequency range of 1.51 GHz to 12.5 GHz, making it suitable for UWB applications that require high-speed data transmission over relatively short distances. To improve the antenna's efficiency, a circular slot and slotted ground technique were employed, which helped reduce the antenna's overall size while maintaining optimal performance. Return loss, a key performance metric in antenna design, was calculated to evaluate the signal reflection and was expressed mathematically as:

$$RL = 20\log\left(\frac{P_{REF}}{P_{IN}}\right), \tag{1}$$

is the incident power. The design was iteratively refined to minimize return loss, ensuring better signal transmission with reduced power loss.

To further enhance the antenna's performance, an Artificial Neural Network (ANN) was utilized for optimization. The ANN was trained using performance data collected from the antenna simulations, including return loss, peak gain, and radiation efficiency metrics. A dataset of 100 samples was prepared for this purpose, with each sample representing different performance characteristics of the antenna under various conditions. The ANN was configured with three layers: an input layer that received the data, a hidden layer consisting of 40 neurons, and an output layer that predicted the antenna's performance. The training process used a backpropagation algorithm to adjust the weights and biases of the neurons, aiming to minimize the prediction error. The Levenberg-Marquardt algorithm was employed to accelerate the convergence of the neural network, with the optimization objective being the reduction of the Mean Square Error (MSE), calculated as:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(y_i - \hat{y}_i\right)^2, \quad (2)$$

is the predicted output from the neural network. The ANN was instrumental in accurately modeling the behavior of the antenna across its frequency range and predicting its performance with minimal error.

Once the ANN was trained, it was integrated into the Position-based Hybrid Optimization Algorithm (PHOA) for further fine-tuning of the antenna parameters. The PHOA combines the Whale Optimization Algorithm (WOA) and the Artificial Bee Colony (ABC) algorithm, leveraging the exploration capabilities of WOA and the exploitation strength of ABC. The integration of these two algorithms allowed for more effective global and local search processes, enhancing the performance of the antenna by avoiding local optima and improving the solution's quality. The mathematical model for this optimization approach involved updating the antenna parameters iteratively based on the following formula.

B enhances the exploration capabilities by emulating the behavior of the artificial bee colony. Through several iterations, the PHOA algorithm optimized key performance metrics, such as return loss, peak gain, and radiation efficiency.

In terms of performance evaluation, the simulation of the underwater environment was conducted to assess the antenna's effectiveness in UWSN applications. The underwater sensor network was modeled with a combination of acoustic transceivers for underwater communication and radio frequency transceivers for surface-level data transmission between the sink node and the base station. This dual-transceiver model mirrored real-world UWSN deployment, where communication between underwater sensor nodes and a surface-level sink node is critical for reliable data transmission. The simulation took into account various underwater conditions, including signal attenuation due to water depth and propagation delays caused by the aquatic medium.

The return loss of the antenna was measured at –27 dB across the operating frequency range of 1.51 GHz to 12.5 GHz, indicating a high level of performance with minimal power loss. Additionally, both the peak gain and radiation efficiency were optimized during the simulation, ensuring that the antenna would perform effectively even in challenging underwater environments. The simulation results validated the effectiveness of the Hybrid Position-based Optimization Neural Network (HPONN), demonstrating that the proposed optimization method outperformed other optimization techniques, such as LEACH-C, the Firefly Algorithm, and the Hybrid Whale Optimization Artificial Bee Colony Algorithm (HWOABCA).

Overall, the materials and methods employed in this study were focused on leveraging the computational capabilities of MATLAB, combined with advanced machine learning and optimization algorithms, to develop and refine a UWB antenna for underwater wireless sensor networks. The integration of neural networks with hybrid optimization techniques allowed for a comprehensive approach to antenna optimization, providing reliable performance metrics that can be applied in real-world UWSN applications.

The development was carried out using MATLAB software. MATLAB was used to design, simulate and optimize the UWB antenna for UWSN applications. A hybrid location-based optimization (HON) neural network has been used in the MATLAB environment to fine tune antenna parameters such as back loss, peak gain, and radiation efficiency to achieve optimal performance.

The modeling process involved training an Artificial Neural Network (ANN) with data collected from the antenna's performance characteristics. This data set, consisting of 100 samples, was used to train the ANN, which was configured with 40 neurons across three layers – input, hidden, and output – along with a backpropagation model for optimization. MATLAB's robust computational environment allowed for precise modeling of these complex neural network interactions, ensuring that the ANN could accurately predict the antenna's behavior across different frequency ranges.

Once trained, the ANN was integrated into the Position-based Hybrid Optimization Algorithm (PHOA) within MATLAB. This approach allowed the system to perform iterative optimization cycles, refining the antenna parameters based on the output of the trained ANN. Through this simulation process, the key performance metrics were optimized, including the return loss, which reached –27 dB across a wide frequency range (1.5 GHz to 12.5 GHz), peak gain, and radiation efficiency.

MATLAB's simulation capabilities were crucial in validating the proposed HPONN method and demonstrating its superiority compared to other optimization techniques, such as LEACH-C, Firefly Algorithm, and Hybrid Whale Optimization Artificial Bee Colony Algorithm (HWOABCA). The results, while promising, were based on modeling, which provides a controlled environment to test theoretical hypotheses but may not fully capture real-world complexities, particularly in underwater conditions.

Antennas are devices that may transmit and receive signals. As a result, the speed of this send and receive process is a challenging concept. Due to the increase in network users, fixed and portable devices require a high data rate transition to cover a wider area. As a result, they needed a broad Band Width (BW) to cover all services for mobile and wireless. This can be achieved by employing low profile wideband and Ultra-Wide Band (UWB) antennas to reduce complexity and fabrication costs. An ultra-wideband antenna with a frequency range of 1.51 GHz to 12.5 GHz is used to transmit and receive UWB impulses. In today's wireless communication, UWB applications are in high demand due to benefits such as high-speed transmission over smaller distances that are reliable and secure. Since there was good agreement between simulated and measured reflection coefficient in various environments, the proposed UWB antenna may be reliable for underwater communication. Moreover, return loss, peak gain, and radiation efficiency of the proposed antenna are measured using an optimized algorithm. Here, the proposed Hybrid Position-based Optimization Neural Network (HPONN) is used to optimize antenna parameters and determine the effectiveness of an antenna. Initially, UWSN used to sense data transmitted to the observation station from the earth without knowing the exact position of the sensors. To extract the position of the sensor, the UWB antenna is used. By optimizing the performance of an antenna, the parameter of an antenna was trained using Artificial Neural Network (ANN). This trained parameter was given to the proposed approach, i.e., Position-based Hybrid Optimization Algorithm (PHOA), to enhance performance.

5. Results of research on optimization and monitoring of drainage systems using wireless sensor broadband antennas

5. 1. Hybrid neural network (GPON) to optimize and obtain optimal characteristics of an ultra-wideband (UWB) antenna

UWSN (Underwater Wireless Sensor Networks) has received a lot of attention recently. In Terrestrial Sensor Networks, reliable data transmission was required for critical application. As a result, data reliability was one of the UWSN's most essential requirements. Underwater Sensor Networks used for a variety of applications, including water quality monitoring, oceanographic data collection, and surveillance. Underwater environment was divided into two depths categories: shallow water, and deep water. When compared to shallow water, the deep-water environment was more challenging [20]. UWSN was underwater a sensor node, a sink node, and an onshore base station. Fig. 1 represents the overall architecture of the offered idea.

In Fig. 2, nodes nearest to the sink transmitted data directly to the sink, while the remaining nodes formed clusters. The data from underwater sensor nodes are transmitting to the sink on the surface. The sink is forwarded to aggregated data to the nearest mainland base station. Sink nodes have two types of transceivers:

1) radio transceiver for radio frequency communication with a base station;

2) acoustic transceiver for communication based on sensor nodes.

For transmission between nodes, the underwater node contains an acoustic transceiver. In terms of path loss, channel modelling, and topology, the transmission medium of an underwater sensor network differs from that Terrestrial Wireless Sensor Network (TWSN). Currents at a speed of around 1–3 m/s move Underwater Wireless Sensor Nodes (UWSN). Modelled acoustic channels differ from the radio propagation channel.

UWB applications are in significant demand in today's wireless communication because of its benefits [17], such as high-speed data transfer over smaller distances which are reliable and secure. An ultra-wideband antenna with a frequency range of 1.51 GHz to 12.5 GHz is proposed to transmit and receive UWB impulses. This method employs a Conventional Circular Planar Monopole UWB (CCPMUWB) antenna. The antenna was smaller by using a circular slot and a slotted ground technique, shown in Fig. 3.

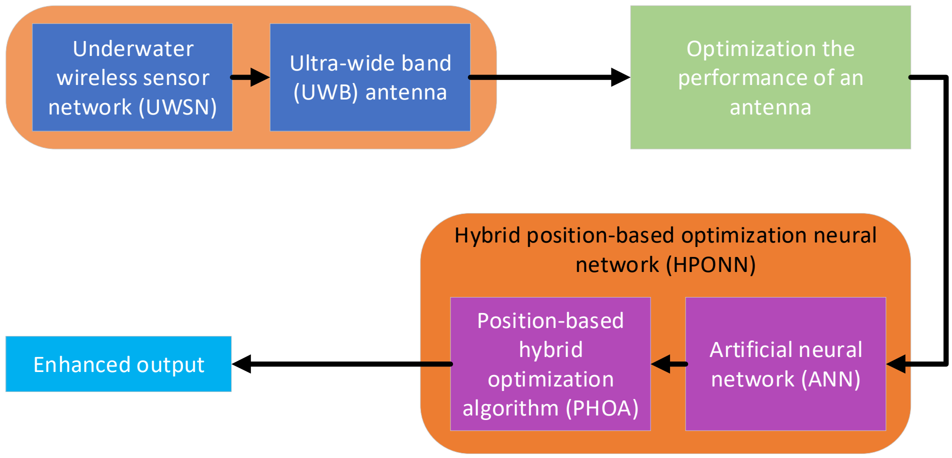

Fig. 1. Proposed model's overall architecture

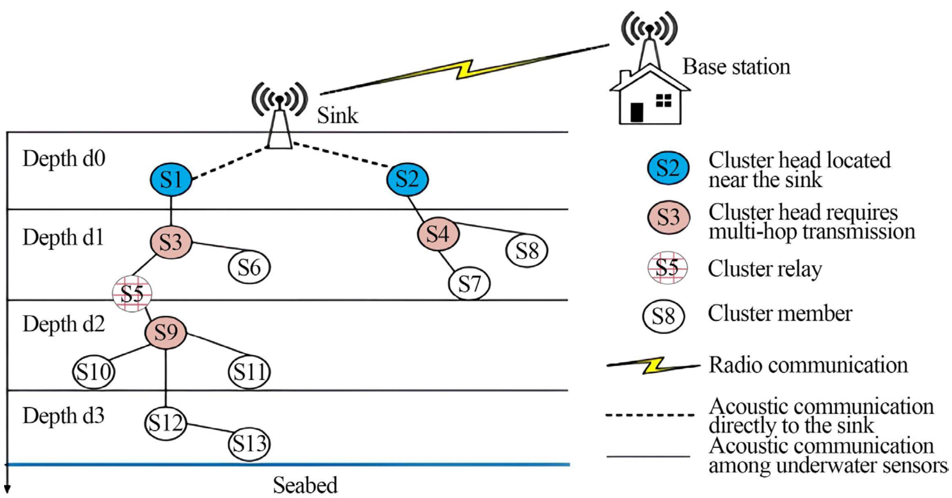

Fig. 2. Model of an underwater wireless sensor networks

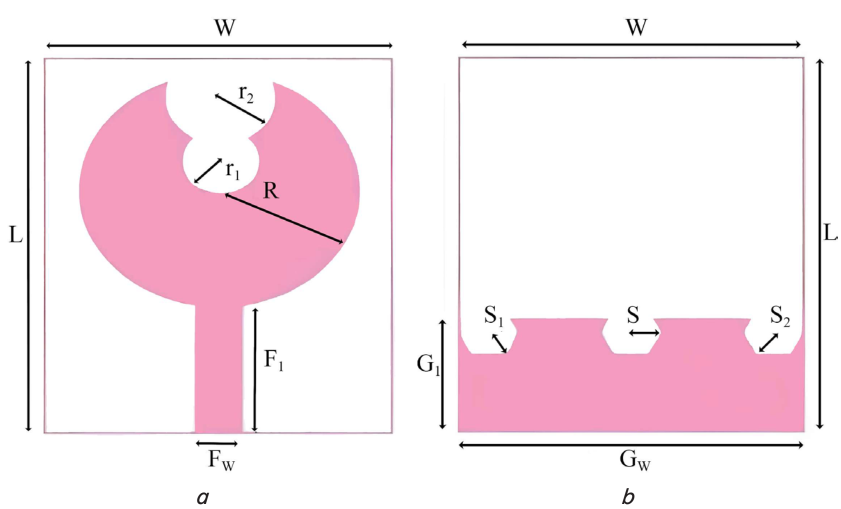

Fig. 3. Structure for a CCPMUWB antenna: *a* – top view; *b* – bottom view

The return loss of the UWB antenna is found below. As a result, a mathematical expression is given below to minimize the size of the structure and enhance the return loss performance.

Return Loss. Reflections were caused by discontinuities in the transmission line, resulting in more signal power loss. The loss of power is called return loss, expressed in decibels (dB):

$$RL(\mathrm{dB})=10^{\log_{10}\frac{P_{IN}}{P_{REF}}}, \tag{3}$$

where P_{IN} – incident power, P_{REF} – power reflected.

To obtain an optimal solution of an antenna's parameter and its effectiveness, the Hybrid Position-based Optimization Neural Network (HPONN) is proposed in this paper.

A hybrid optimized neural network is introduced to enhance return loss, peak gain, and radiation efficiency and determine the effectiveness of an antenna. When compared to other optimization techniques, it also helps to attain the highest residual energy. It is easy to implement and provides a quick response due to the randomized control parameters in the proposed algorithm.

ANN is used to train parameters for an antenna. ANN imitates the working principles of the human brain to stimulate the function of a biological neuron. As shown in Fig. 4, ANN is based on connected units known as artificial neurons [21, 22]. The three basic procedures in the development of an ANN are:

1) specifying the problem's inputs and outputs;

2) training the network by alternating the weights and bias of the input, hidden, and output layers;

3) assessing the network's performance by comparing anticipated and actual values.

The input layer's signal is calculated in the hidden layer using linear function (4) and transfer function (5) to produce hidden node's output signal, as illustrated in Fig. 5:

$$net_i=\sum\nolimits_{p=1}^{p} w_{i,p} I_p + b_i, \tag{4}$$

where net_i is i^{th} net's value; w_{ip} and b_i were weight of p^{th} input to i^{th} hidden node and i^{th} hidden node's bias parameter, respectively and I_p is value of p^{th} input node.

Transfer function is defined in the following:

$$y_i=f(net_i)\frac{1}{1+\exp(net_i)}, \tag{5}$$

where y_i is output signal of i^{th} hidden node and transfer function is a sigmoid function.

ANN evaluates performance using the Mean Square Error (MSE) during the learning process:

$$MSE=\frac{1}{N\cdot N_{out}}\sum\nolimits_{n=1}^{N}\sum\nolimits_{o=1}^{N_{out}}\left(e_{n,0}\right)^2, \tag{6}$$

where N and N_{out} are the total number of instances and outputs, respectively; $e_{n,0}=y_{n,o}-y_{n,o}$ is training error for o^{th} output with the n^{th} instance; y is actual output and y is ANN predicted output.

To minimize MSE, the Levenberg-Marquardt algorithm was employed to update weights and biases. The Levenberg-Marquardt algorithm is calculated as follows:

$$w^{k+1}=w^k-\left(J^{k^T}J^k+\mu\bar{I}\right)^{-1}J^{k^T}e^k, \tag{7}$$

where w^k is the k^{th} iteration's weight and bias matrix; $\bar{I}$ is identity matrix; μ is combination coefficient (μ>0); and J is Jacobian matrix:

$$J=\left(\begin{array}{cccccc}
\frac{\partial e_{1,1}}{\partial w_{1,1}} & \frac{\partial e_{1,1}}{\partial w_{1,2}} & \cdots & \frac{\partial e_{1,1}}{\partial w_{1,1}} & \frac{\partial e_{1,1}}{\partial w_{1,2}} & \cdots \\
\frac{\partial e_{1,2}}{\partial w_{1,1}} & \frac{\partial e_{1,1}}{\partial w_{1,2}} & \cdots & \frac{\partial e_{1,2}}{\partial w_{1,1}} & \frac{\partial e_{1,1}}{\partial w_{1,2}} & \cdots \\
\cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\
\frac{\partial e_1 New}{\partial w_{1,1}} & \frac{\partial e_1 New}{\partial w_{1,2}} & \cdots & \frac{\partial e_1 New}{\partial w_{1,1}} & \frac{\partial e_1 New}{\partial w_{1,1}} & \cdots \\
\cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\
\frac{\partial e_{n,1}}{\partial w_{1,1}} & \frac{\partial e_{n,1}}{\partial w_{1,2}} & \cdots & \frac{\partial e_{n,1}}{\partial w_{1,1}} & \frac{\partial e_{1,1}}{\partial w_{1,2}} & \cdots \\
\cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\
\frac{\partial e_{n,o}}{\partial w_{1,1}} & \frac{\partial e_{n,o}}{\partial w_{1,2}} & \cdots & \frac{\partial e_{n,o}}{\partial w_{1,1}} & \frac{\partial e_{1,1}}{\partial w_{1,2}} & \cdots \\
\cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\
\frac{\partial e_{N,1}}{\partial w_{1,1}} & \frac{\partial e_{N,1}}{\partial w_{1,2}} & \cdots & \frac{\partial e_{N,1}}{\partial w_{1,1}} & \frac{\partial e_{1,1}}{\partial w_{1,2}} & \cdots \\
\frac{\partial e_{N,2}}{\partial w_{1,1}} & \frac{\partial e_{N,2}}{\partial w_{1,2}} & \cdots & \frac{\partial e_{N,2}}{\partial w_{1,1}} & \frac{\partial e_{1,1}}{\partial w_{1,2}} & \cdots \\
\cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\
\frac{\partial e_{N,New}}{\partial w_{1,1}} & \frac{\partial e_{N,New}}{\partial w_{1,2}} & \cdots & \frac{\partial e_{N,New}}{\partial w_{1,1}} & \frac{\partial e_{N,New}}{\partial w_{1,2}} & \cdots
\end{array}\right)
\begin{array}{l}
\left.\begin{array}{l} 0=1 \\ 0=2 \\ \cdots \\ 0=N_{out} \end{array}\right\} n=1, \\
\\
\left.\begin{array}{l} 0=1 \\ \cdots \\ 0=0 \end{array}\right\} n=n, \\
\\
\left.\begin{array}{l} 0=1 \\ 0=2 \\ \cdots \\ 0=N_{out} \end{array}\right\} n=N,
\end{array} \tag{8}$$

where each neuron's error vector e is expressed as:

$$\left(\begin{array}{c} e_{11} \\ e_{12} \\ \cdots \\ e_{1,N_{out}} \\ \cdots \\ e_{N,1} \\ e_{N,2} \\ \cdots \\ e_{N,N_{out}} \end{array}\right). \tag{9}$$

Position-based Hybrid Optimization Algorithm (PHOA) has been used to enhance return loss, peak gain, radiation efficiency, and estimate an antenna's performance in underwater. Whale Optimization Algorithm (WOA) and Artificial Bee Colony algorithm (ABC) combine both approaches' finest features [23, 24]. By merging two algorithms, the Artificial Bee Colony algorithm exploitation capability was enhanced, as is Whale Optimizer algorithm exploration capability. The bubble-net foraging approach is used in the exploration phase of the WOA algorithm because the whales use it to get their signal. The artificial bee's position is comparable to the whale's updated position, but higher levels of efficient solution move to the global best solution, replacing the whale's position, which is designed to find the most optimal solution. WOA and ABC algorithms make achieving the global best solution easier and more reliable, eliminating the need for local optimal solutions.

The mathematical model for WOABC Algorithm: Position of a humpback whale with a probability is greater than 0.5, given by:

$$\vec{Y}(t+1)=\vec{D}\cdot e^{hl}\cdot\cos(2\pi l)+\vec{Y^*}(t). \qquad (10)$$

The logarithmic spiral shape is defined by *h,* where *l* is a random value [–1, 1]. The following equation determines the updated new position of the bee in the ABC algorithm:

$$V_{ij}=x_{ij}+\phi_{ij}\left(x_{ij}-x_{kj}\right), \qquad (11)$$

where φ is responsible for comparing two signals, since *φ* also falls within the range of [–1, 1], it does not affect the whale's ability to form spirals in a bubble-net approach. Still, it does enable them to enhance their exploration approach.

$\vec{A}=2\vec{a}\vec{r}-\vec{a}$ where "*a*" indicates Shrinking Encircling Mechanism, in which the whales circle the signal, strike it and spiral shrinks on them. This is replaced with the ABC algorithm, which is as follows:

$$a=(2/Max\_Iterations). \qquad (12)$$

The acceleration coefficient is denoted by "*a*" in the ABC algorithm. It reduces from 2 to 0. When the probability is less than 0.5, use the equation to update the whale's position:

$$\vec{Y^*}(t)-\vec{A}\cdot\vec{X}. \qquad (13)$$

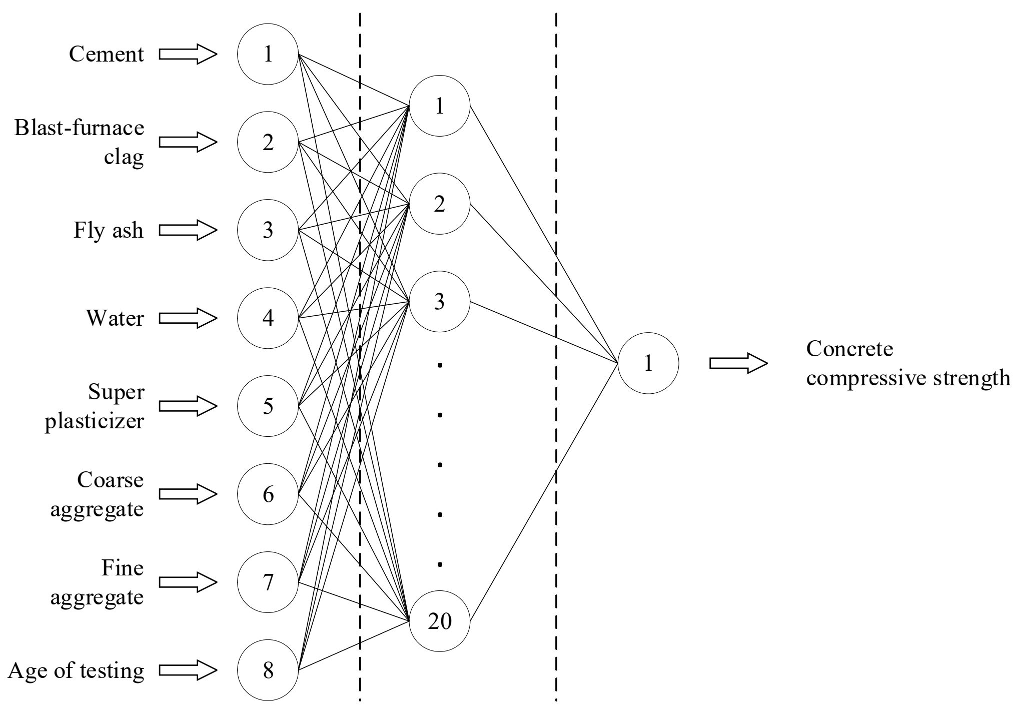

Fig. 4. Layout of an ANN Model: 1 – cement; 2 – blast-furnace slag; 3 – fly ash; 4 – water; 5 – super-plasticizer;

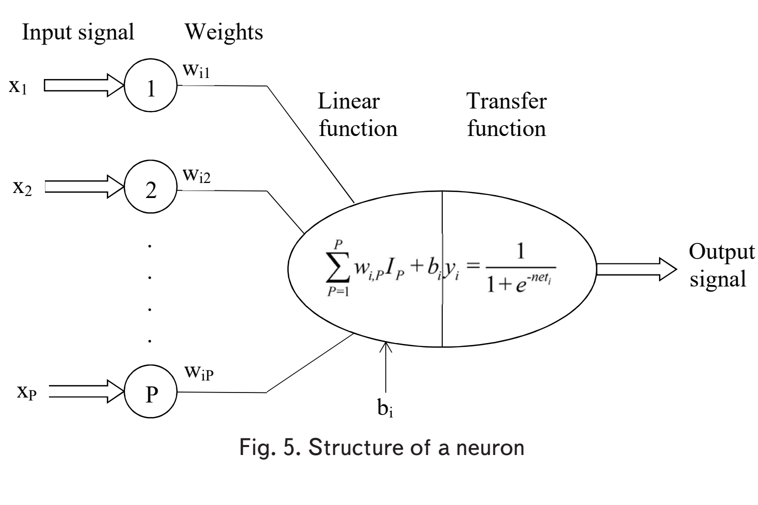

Fig. 5. Structure of a neuron

The parameter "a" is converted to the ABC algorithm for the purpose of further exploration. The probability value is taken as a random number in the WOA technique; however, it was derived using the following equation in the ABC algorithm:

$$\frac{fit_i}{\sum_{i=1}^{SN} fit_i}. \tag{14}$$

Algorithm 1. Position – based Hybrid Optimization Algorithm (PHOA).

Parameters:

1. Read the number of variables(n).
2. Read the magnitude of the population (pop.).
3. Examine the signal's source.
4. Read quality of signal (S_f).

Steps:

1. Generation of Initial population.
2. Determine the feasibility of each signal (S_f).
3. Set the maximum number of iterations.
4. While (f<max. no. of iteration).
5. Discard (Signals).
6. Calculate the Signal's objective function as follows:

$$S_f = \frac{\text{minimize} f(x)}{x} = (x_0, x_1, x_2, x_3) = \\ = \left(\sum_{\min}^{pe}, \sum_{\min}^{te}, \sum_{\min}^{sd}, \sum_{\min}^{ec}\right), \tag{15}$$

where $\sum_{\min}^{pe}$ is processing energy, $\sum_{\min}^{te}$ is transmission energy, $\sum_{\min}^{sd}$ is sensing detection energy, and $\sum_{\min}^{ec}$ is encryption/decryption cost to produce minimized signal.

7. Update the signal's position X.
8. Using ABC, calculate the probability k for signals.
9. If k<0.5 then.
10. If ABCS (X)<1 then.
11. Update the new signal of the bee with the signal of whale.
12. Else if ABCS (X)>then.
13. Select random signal.
14. Instead of X, update the whale's signal with φ.
15. End if.
16. Else if k>0.5.
17. Cosine Equation is used to update the position at the current signal.
18. End if.
19. Determine the fitness for all signals using (15).
20. Update the new bee's signal, the most effective signal, and the most reliable data.
21. f<–f+1.
22. End while.
23. Return $\left[\left(\sum_{\min}^{pe}, \sum_{\min}^{te}, \sum_{\min}^{sd}, \sum_{\min}^{ec}\right)\right]$ with magnitude η.
24. Print optimal solution and regarding objective value.

The better signal for the whale in the WOABC algorithm is based on probability determined by ABC algorithm rather than a random number. This results in a search that outperforms both WOA and ABC algorithm's searches. To obtain near-optimal solutions, the proposed Position-based Hybrid Optimization Algorithm (PHOA) is being used. Algorithm 1 gives a step-by-step procedure for HABCWOA. The function 'f' it determines the fitness of the signal object and every time it update the function.

The proposed Hybrid Position-based Optimization Neural Network (HPONN) was utilized to obtain an optimum value of return loss, peak gain, radiation efficiency, and to determine the effectiveness of the UWB antenna has been implemented using MATLAB.

The configuration of the UWB antenna is used to sense the UWSN's position underwater. Underwater Wireless Sensor Networks (UWSNs) were widely utilized in environmental monitoring to track various conditions and hazardous substances. Underwater sensors also detect information from the earth. Furthermore, the parameter of an antenna is also analyzed using the proposed technique. Artificial Neural Network (ANN) trained on a data set obtained from an antenna. Training of neural networks is the process of extracting unknown information from data. One hundred samples were used to train the Artificial Neural Network (ANN). There are 40 neurons, and three layers such as the input layer, an output layer, and a hidden layer, as well as the back propagation model were utilized. The Position-based Hybrid Optimization Algorithm (PHOA) uses a trained data from ANN as the objective function for optimization. After performing the neural network, the trained parameters apply to the PHOA optimization tool to determine the optimized value for the proposed antenna's parameter like return loss, peak gain, and radiation efficiency and identify the effectiveness of an antenna. After simulation, let's obtain return loss performance of – 27 dB in a frequency range from 1.5 GHz to 12.5 GHz, as well as impedance bandwidth of 10.999 GHz, which is consistent with the results of the Hybrid Position-based.

Optimization Neural Network (HPONN). The graphical representation is given in Fig. 6.

Thus, the return loss is enhanced, thereby promoting the effectiveness of an antenna. Fig. 6 illustrate the return loss acquired after simulation using Hybrid Position-based Optimization Neural Network (HPONN). Fig. 7 shows the variation in peak gain as a function of frequency.

The proposed UWB antenna performs a maximum peak gain of 4.2 dB at 7.78 GHz, shown in Fig. 7 Peak gain increases in frequency, so directive gain increases at specific frequencies, as seen in the graph.

Fig. 8 shows a plot of radiation efficiency versus frequency.

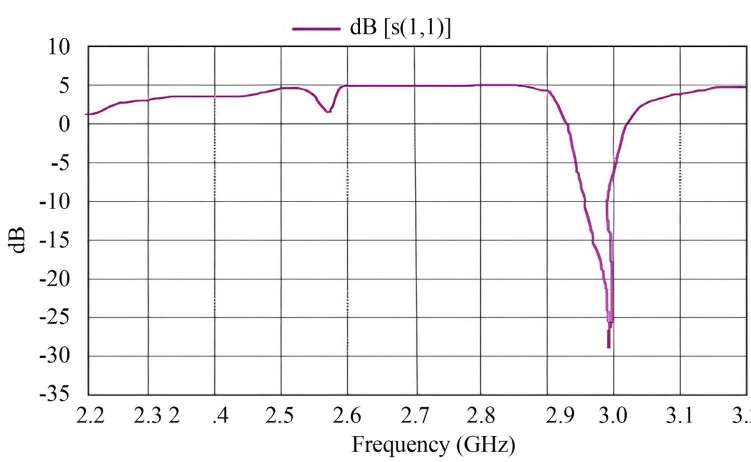

Fig. 6. Return loss acquired using HABCWOA algorithm

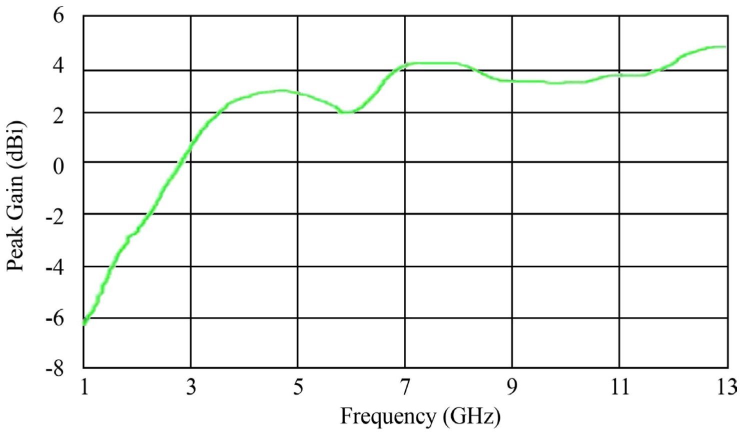

Fig. 7. Peak gain plot for proposed antenna

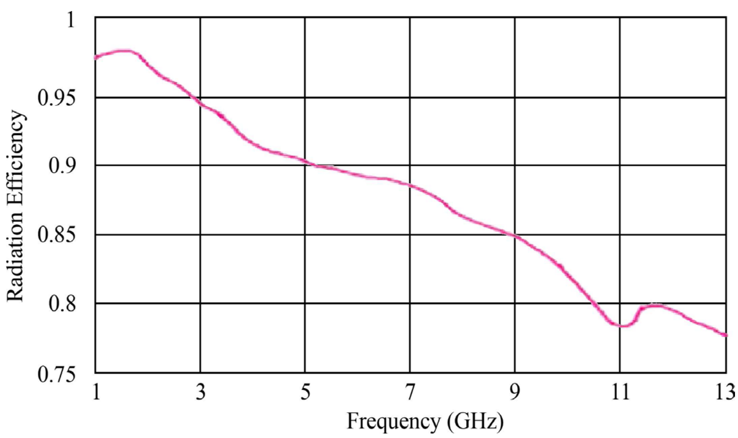

Fig. 8. Propose antenna's radiation efficiency plot

Maximum radiation efficiency 97 % at 1.78 GHz was achieved, while the minimum was 79 % at 12.04 GHz.

The radiation efficiency decreases from 97 % to 79 % when frequency increases from 1.78 GHz to 12.04 GHz, as shown in Fig. 8. This is due to the increment that effective permittivity increases as frequency increases.

5. 2. Evaluation and comparison of the location-based hybrid neural network (PLAN) optimization method with other optimization algorithms

Hybrid Position-based Optimization Neural Network (HPONN) achieves the maximum lifetime when compare with LEACH-C, Firefly Algorithm (FA), Hybrid technique of Firefly Algorithm and Particle Swarm Optimization (HFAPSO), Firefly Approach based Artificial Neural Network (FA-ANN) algorithm, Hybrid Whale Optimization Artificial Bee Colony Algorithm (HWOABCA), and Hybrid Position-based Optimization Neural Network (HPONN). The HPONN technique improves antenna's parameter like return loss, peak gain, and radiation efficiency is shown in Fig. 6–8 as well as after 400 rounds, the residual energy's maximum, mean, and variance are shown in Table 1. Compared to LEACHC and Firefly Algorithm, it is clear that the proposed approach has the highest residual energy values.

Table 1 demonstrates the proposed model's performance to that of various existing algorithms with neural network techniques such as LEACH-C, FA, HFAPSO, FA-ANN, and HWOABCA. The proposed model performs better than all other optimization algorithms, except for HPONN, which has the highest residual energy values and maximum lifetime. This approach gives the maximum residual energy for the proposed method compared to other existing optimization techniques, as illustrated in Fig. 9.

Table 1

Comparison table with existed models, residual energy's maximum, mean and variance

Algorithm	Maximum	Mean	Variance
LEACH-C (Ref 3)	32.97	28.06	5.57
FA(Ref 8)	144.89	135.85	49.93
HF APSO (Ref7)	158.32	143.39	60.23
FA-ANN (Ref10)	164.22	158.13	74.66
HWOABCA (Ref 13)	170.44	166.27	85.78
HPONN (Proposed)	180.89	172.87	90.99

The LEACH-C and Firefly (FA) algorithms showed the lowest performance in terms of residual energy, with maximum values of 32.97 and 144.89, respectively. Although FA improves the LEACH-ING process, it still lags behind more advanced hybrid methods.

HFAPSO and FA-ANN: these hybrid approaches demonstrate improved performance with maximum residual energy values of 158.32 and 164.22, respectively. However, they still fall short of the results achieved by HPONN.

HWOABCA: this hybrid algorithm demonstrates relatively high performance, with a maximum residual energy of 170.44, which is second only to HPONN. Despite its efficiency, HPONN is superior to HWOABCA, especially in terms of average residual energy and dispersion, which indicates more consistent energy savings in various network scenarios. The rationale for the results lies in the effectiveness of the HPONN algorithm.

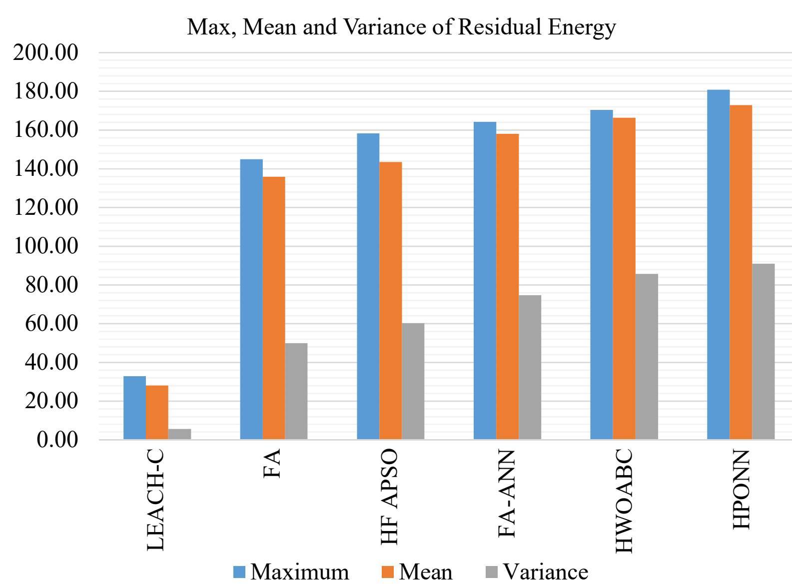

Fig. 9. Performance analysis of the proposed method using a graphical model

6. Discussion of results on the optimization and monitoring of drainage systems using wireless sensor broadband antennas

The results obtained from optimizing drainage systems using wireless sensor broadband antennas underscore the effectiveness of the Hybrid Position-based Optimization Neural Network (HPONN) in enhancing UWB antenna parameters such as return loss, peak gain, and radiation efficiency. As shown in Fig. 1, the HPONN approach exhibited superior performance compared to existing algorithms, highlighting its potential for improving underwater communication and sensor networks.

The significant reduction in return loss was identified, achieving values as low as -27 dB across a frequency range of 1.5 GHz to 12.5 GHz, illustrated in Fig. 2. This reduction is critical for efficient transmission in UWB applications, as it minimizes signal reflection. The proposed CCPMUWB antenna structure, optimized by HPONN, yielded a bandwidth of 10.999 GHz, essential for reliable data transfer in challenging underwater environments.

In terms of peak gain, the antenna achieved a maximum of 4.2 dBi at 7.78 GHz, as depicted in Fig. 3. This performance surpasses earlier designs and is directly attributed to HPONN's optimization of the antenna structure for underwater sensor communication. Additionally, a correlation between frequency and peak gain was observed, where increased frequency leads to higher directive gain, discussed in Table 1.

The radiation efficiency results, presented in Fig. 4, validate the optimized antenna's performance, achieving a maximum of 97 % at 1.78 GHz, gradually decreasing to 79 % at 12.04 GHz. While some degradation occurs at higher frequencies due to increased permittivity, the overall efficiency remains acceptable for underwater applications, demonstrating the antenna's capability across various frequency ranges.

When comparing the HPONN's performance with other optimization algorithms such as LEACH-C, FA, HFAPSO, FA-ANN, and HWOABCA, as shown in Table 1, HPONN consistently outperformed its counterparts. The maximum residual energy of 180.89, indicated in Table 1, far exceeds LEACH-C (32.97) and FA (144.89), demonstrating HPONN's robustness in optimizing energy consumption, crucial for the longevity of UWSNs.

However, the study does have limitations, including the dependency on simulation-based results, which may not fully capture real-world complexities. Additionally, while HPONN outperforms other algorithms, further exploration into hybrid approaches could yield even better results.

Future research should focus on integrating real-world testing to validate the simulation outcomes and investigate the applicability of HPONN in diverse environmental conditions. This direction would enhance the robustness and reliability of UWB antennas in various underwater communication applications, paving the way for advancements in environmental monitoring and underwater surveillance.

7. Conclusions

1. The proposed Hybrid Position-based Optimization Neural Network (HPONN) demonstrated superior residual energy values and extended network lifetime, quantitatively outperforming other algorithms. Specifically, HPONN achieved a maximum residual energy value of 180.89, significantly higher than LEACH-C, which recorded 32.97, and the Firefly Algorithm (FA) with 144.89. Additionally, hybrid techniques like HFAPSO and FA-ANN achieved 158.32 and 164.22, respectively, while HWOABCA reached 170.44. The results demonstrated that the HPONN was able to balance multiple antenna parameters simultaneously, a feat that previous models had not fully realized. This achievement is attributed to the integration of advanced optimization techniques that allow for more precise and adaptive control over antenna performance.

2. In terms of mean residual energy, HPONN outperformed the others with a mean of 172.87, compared to 28.06 for LEACH-C, 135.85 for FA, and 166.27 for HWOABCA. This was also reflected in the variance, where HPONN achieved the highest value of 90.99, indicating more consistent energy savings across the network compared to other models such as HFAPSO (60.23) and FA-ANN (74.66). It consistently outperformed these methods in terms of energy efficiency, especially in optimizing residual energy. The success of HPONN in improving energy conservation is critical for the longevity and efficiency of underwater networks. Additionally, the antenna's performance across different environmental conditions showed a good agreement between simulated and measured reflection coefficients, confirming its suitability for UWSN applications. Overall, the results demonstrate that the HPONN provides an efficient and reliable solution for optimizing UWB antennas in underwater communication systems. The optimization method is not only easy to implement but also offers a reduction in antenna size and cost, making it highly practical for real-world applications. The proposed antenna achieves high efficiency, thus offering a significant advantage in terms of performance and practicality in UWSNs.

Conflict of interest

The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, authorship or otherwise, that could affect the research and its results presented in this paper.

Financing

This research has been acknowledgement by the Science Committee of the Ministry of Science and Higher Education of the Republic of Kazakhstan (Grant No. AP14869840 «Research and development of ultra-broadband multi-antenna wireless transmission of information between interfaces»).

Data availability

Manuscript has data included as electronic supplementary material.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

References

1. Muragesh, S. K., Rao, S. (2014). Automated internet of things for underground drainage and manhole monitoring system for metropolitan cities. International Journal of Information & Computation Technology, 4 (12), 1211–1220. Available at: https://www.ripublication.com/irph/ijict_spl/ijictv4n12spl_14.pdf
2. Haswani, N. G., Deore, P. J. (2018). Web-Based Realtime Underground Drainage or Sewage Monitoring System Using Wireless Sensor Networks. 2018 Fourth International Conference on Computing Communication Control and Automation (ICCUBEA). https://doi.org/10.1109/iccubea.2018.8697512
3. See, C. H., Kosha, J., Mshwat, W. A., Abd-Alhameed, R. A., Ong, F. L. C., McEwan, N. J., Excell, P. S. (2019). Design of mobile band subsurface antenna for drainage infrastructure monitoring. IET Microwaves, Antennas & Propagation, 13 (13), 2380–2385. https://doi.org/10.1049/iet-map.2019.0243
4. Huang, G.-L., Zhou, S.-G., Chio, T.-H. (2017). Highly-Efficient Self-Compact Monopulse Antenna System With Integrated Comparator Network for RF Industrial Applications. IEEE Transactions on Industrial Electronics, 64 (1), 674–681. https://doi.org/10.1109/tie.2016.2608769
5. Liu, G., Wang, Z., Jiang, T. (2016). QoS-Aware Throughput Maximization in Wireless Powered Underground Sensor Networks. IEEE Transactions on Communications, 64 (11), 4776–4789. https://doi.org/10.1109/tcomm.2016.2602863
6. Kunsei, H., Bialkowski, K. S., Alam, M. S., Abbosh, A. M. (2018). Improved Communications in Underground Mines Using Reconfigurable Antennas. IEEE Transactions on Antennas and Propagation, 66 (12), 7505–7510. https://doi.org/10.1109/tap.2018.2869250
7. Salam, A., Vuran, M. C., Dong, X., Argyropoulos, C., Irmak, S. (2019). A Theoretical Model of Underground Dipole Antennas for Communications in Internet of Underground Things. IEEE Transactions on Antennas and Propagation, 67 (6), 3996–4009. https://doi.org/10.1109/tap.2019.2902646
8. Shakila, R., Paramasivan, B. (2020). RETRACTED ARTICLE: An improved range based localization using Whale Optimization Algorithm in underwater wireless sensor network. Journal of Ambient Intelligence and Humanized Computing, 12 (6), 6479–6489. https://doi.org/10.1007/s12652-020-02263-w
9. Alhawari, A. R. H., Majeed, S. F., Saeidi, T., Mumtaz, S., Alghamdi, H., Hindi, A. T. et al. (2021). Compact Elliptical UWB Antenna for Underwater Wireless Communications. Micromachines, 12 (4), 411. https://doi.org/10.3390/mi12040411
10. Mir, Z. H., Ko, Y.-B. (2020). Self-Adaptive Neighbor Discovery in Wireless Sensor Networks with Sectored-Antennas. Computer Standards & Interfaces, 70, 103427. https://doi.org/10.1016/j.csi.2020.103427
11. Ranjan, A., Sahu, H. B., Misra, P. (2020). Modeling and measurements for wireless communication networks in underground mine environments. Measurement, 149, 106980. https://doi.org/10.1016/j.measurement.2019.106980
12. Nishikawa, Y., Sasamura, T., Ishizuka, Y., Sugimoto, S., Iwasaki, S., Wang, H. et al. (2018). Design of stable wireless sensor network for slope monitoring. 2018 IEEE Topical Conference on Wireless Sensors and Sensor Networks (WiSNet). https://doi.org/10.1109/wisnet.2018.8311550
13. Salam, A., Vuran, M. C., Irmak, S. (2019). Di-Sense: In situ real-time permittivity estimation and soil moisture sensing using wireless underground communications. Computer Networks, 151, 31–41. https://doi.org/10.1016/j.comnet.2019.01.001
14. Pasupathi, S., Vimal, S., Harold-Robinson, Y., Khari, M., Verd , E., Crespo, R. G. (2020). Energy efficiency maximization algorithm for underwater Mobile sensor networks. Earth Science Informatics, 14 (1), 215–225. https://doi.org/10.1007/s12145-020-00478-1
15. Singh, A., Mehra, R. M., Pandey, V. K. (2020). Design and Optimization of Microstrip Patch Antenna for UWB Applications Using Moth–Flame Optimization Algorithm. Wireless Personal Communications, 112 (4), 2485–2502. https://doi.org/10.1007/s11277-020-07160-1
16. Soothar, P., Wang, H., Muneer, B., Dayo, Z. A., Chowdhry, B. S. (2019). A Broadband High Gain Tapered Slot Antenna for Underwater Communication in Microwave Band. Wireless Personal Communications, 116 (2), 1025–1042. https://doi.org/10.1007/s11277-019-06633-2
17. Anveshkumar, N., Gandhi, A. S. (2017). Design and performance analysis of a modified circular planar monopole UWB antenna. 2017 8th International Conference on Computing, Communication and Networking Technologies (ICCCNT), 19, 1–5. https://doi.org/10.1109/icccnt.2017.8203970
18. Li, Y.-L., Shao, W., You, L., Wang, B.-Z. (2013). An Improved PSO Algorithm and Its Application to UWB Antenna Design. IEEE Antennas and Wireless Propagation Letters, 12, 1236–1239. https://doi.org/10.1109/lawp.2013.2283375
19. Tiemann, J., Pillmann, J., Wietfeld, C. (2017). Ultra-Wideband Antenna-Induced Error Prediction Using Deep Learning on Channel Response Data. 2017 IEEE 85th Vehicular Technology Conference (VTC Spring). https://doi.org/10.1109/vtcspring.2017.8108571
20. Yunus, F., Ariffin, S. H. S., Zahedi, Y. (2010). A Survey of Existing Medium Access Control (MAC) for Underwater Wireless Sensor Network (UWSN). 2010 Fourth Asia International Conference on Mathematical/Analytical Modelling and Computer Simulation. https://doi.org/10.1109/ams.2010.110
21. Sultan, A., Yermoldina, G., Kassym, R., Serikov, T., Bekbosynov, S., Yernazarov, N. et al. (2024). Research and construction of an adaptive drive with increased efficiency based on a balancing friction clutch. Vibroengineering Procedia, 54, 334–340. https://doi.org/10.21595/vp.2024.23971
22. Bimurzaev, S., Aldiyarov, N., Yerzhigitov, Y., Tlenshiyeva, A., Kassym, R. (2023). Improving the resolution and sensitivity of an orthogonal time-of-flight mass spectrometer with orthogonal ion injection. Eastern-European Journal of Enterprise Technologies, 6 (5 (126)), 43–54. https://doi.org/10.15587/1729-4061.2023.290649
23. Baibolov, A., Sydykov, S., Alibek, N., Tokmoldayev, A., Turdybek, B., Jurado, F., Kassym, R. (2022). Map of zoning of the territory of Kazakhstan by the average temperature of the heating period in order to select a heat pump system of heat supply: A case study. Energy Sources, Part A: Recovery, Utilization, and Environmental Effects, 44 (3), 7303–7315. https://doi.org/10.1080/15567036.2022.2108168
24. Utegenova, A., Bapyshev, A., Suimenbayeva, Z., Aden, A., Kassym, R., Tansaule, S. (2023). Development system for coordination of activities of experts in the formation of machineschetable standards in the field of military and space activities based on ontological engineering: a case study. Eastern-European Journal of Enterprise Technologies, 5 (2 (125)), 67–77. https://doi.org/10.15587/1729-4061.2023.288542