

Meta-Heuristic Optimization of WBAN Coordinator Placement with 3-D Visualization

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Abstract—This paper introduces an interactive 3-D modular framework for optimizing Body Node Coordinator (BNC) placement and sensor transmission power in Wireless Body Area Networks (WBANs). Using meta-heuristic algorithms Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) to solve a multi-objective problem that maximizes connectivity and minimizes energy use. The propagation model follows the IEEE 802.15.6 standard for on-body channels. Its architecture comprises independent modules for a Graphical User Interface (GUI), 3-D rendering, propagation calculation, and optimization, producing visual reports of network topology and performance metrics. The tool offers a practical decision-support solution for WBAN sizing and deployment in Internet of Body (IoB) applications such as medical wearables, industrial automation, and security systems.

Keywords—BNC, WBAN, Metaheuristic Algorithms, PSO, GA, IEEE 802.15.6 and IoB.

I. INTRODUCTION

The Internet of Body (IoB) represents the evolution of the Internet of Things (IoT) into the human domain, establishing direct connectivity between sensors, actuators, and electronic devices and the human organism [1]. At the core of this infrastructure lies the Wireless Body Area Network (WBAN), a short-range wireless communication network specifically engineered to operate on or within the human body. Unlike conventional networks, a WBAN must satisfy stringent requirements concerning ultra-low power consumption, high reliability, extreme miniaturization, robustness to motion, and the security of biometric data.

WBANs form the backbone of the emerging IoB paradigm, which seeks to seamlessly integrate wearable and implantable devices with digital health services, continuous physiological monitoring, and personalized well-being applications [2]. In this context, the ability to reliably collect, transmit, and process biomedical data in real time depends critically on the proper

dimensioning of the communication infrastructure, specifically the strategic placement of gateways and the configuration of sensor transmission power [3]. Inadequate dimensioning can lead to loss of connectivity, increased latency, and, most importantly, excessive energy consumption that shortens device autonomy and undermines the reliability of mission-critical applications. WBANs are already deployed in a wide range of scenarios, including remote monitoring of chronic patients, robot-assisted surgeries, early fall detection for the elderly, insulin-therapy management, and augmented-reality systems for physical rehabilitation.

The IoB is increasingly recognized as a transformative paradigm in which WBANs turns the concept of a body-centric internet into a practical reality. A substantial body of research has therefore concentrated on the problem of locating the network's central element referred to as the Body Node Coordinator (BNC) or hub because its position strongly influences energy consumption, link reliability, and overall Quality of Service (QoS).

Choudhary et.al.[4] presented a complete WBAN routing scheme that jointly optimizes the BNC location and the selection of cluster-head nodes using a Multi-Objective Particle Swarm Optimizer (MO-PSO). Each particle encodes the BNC's (x,y) coordinates and a cluster-head identifier, and the fitness function simultaneously minimizes network energy consumption and average bit-error rate (BER), achieving a trade-off between energy efficiency and communication reliability.

Shukla et.al.[5] tackled the same placement problem from an energy-lifetime perspective with a Whale Optimization Algorithm (WOA). A population of "whale search agents" performs encircling-prey, bubble-net feeding (exploitation), and random-prey search (exploration) to rapidly converge on a hub position that reduces the total transmission energy of biosensor nodes, thereby extending WBAN operational lifetime.

Zhang et.al.[6] extended the concept by embedding sensing and hub functions into multifunctional smart fabrics, replacing conventional radio links with a human-body channel that improves privacy and energy efficiency. Their joint optimization model minimizes total cost while balancing energy consumption, latency, path loss, and QoS across four typical daily activities, dynamically activating different hub regions to adapt to changing activity states and simultaneously addressing energy, performance, and device miniaturization.

Across the cited works, the central node's location is consistently treated as a key design variable because it di-

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rectly affects energy consumption and link quality. All studies employ population-based meta-heuristics (e.g., MO-PSO, WOA, or custom joint optimizers) to solve the non-convex, multi-objective placement problem. Energy minimization is the primary goal, often complemented by secondary QoS metrics such as BER, network lifetime, latency, or path loss. However, most approaches assume a static sensor layout and do not consider dynamic topology changes or posture-induced channel variations.

Responding to the growing demand for solutions that guarantee full coverage while preserving energy efficiency, this work proposes a modular framework that jointly optimizes BNC positioning and sensor transmission power by formulating the problem as a multi-objective optimization that maximizes network connectivity and minimizes energy consumption. The main contribution in integrating the meta-heuristic algorithms Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) within an architecture composed of independent modules for three-dimensional rendering, IEEE 802.15.6 on-body propagation calculation, optimization, and result visualization. Experimental results demonstrate that the proposed approach yields optimal or near-optimal solutions, achieving an effective trade-off between coverage and energy efficiency, and providing a flexible tool for intelligent dimensioning of WBANs in IoB environments.

This paper is organized as follows: Section II describes the modular architecture of the framework and its components. Section III presents the optimization evaluation metrics and the performance of the generated network for each simulation. Finally, Section IV presents the conclusions and perspectives for future work.

II. METHODOLOGY

The developed framework is based on a modular architecture consisting of four main components, which are described in this section: Graphical User Interface (GUI), 3-D Rendering, Propagation Calculation and Optimization.

A. Graphical User Interface

The GUI is built with PyQt5 and offers an interactive experience for the user [7]. It allows configuration of devices, 3-D visualization of models, adjustment of optimization parameters and analysis of the results. The application's GUI is divided into three main areas, as shown in Fig. 1:

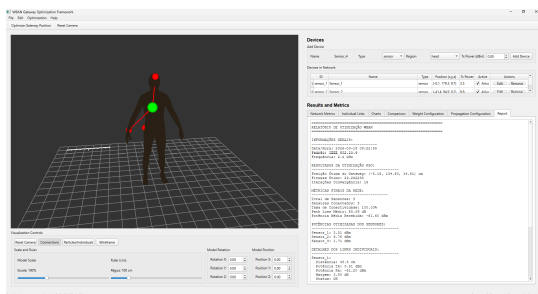


Fig. 1: The main application's GUI.

1) *3-D Visualization (left side)*: An OpenGL renderer shows the human-body model and placed devices. View-control buttons let users reset the camera, toggle connection lines, particle display, and wire-frame mode. Model-control sliders adjust scale, ruler length, rotation and translation ($x/y/z$). Devices can be added directly in the scene with Ctrl (sensor) or Alt (gateway) + click.

2) *Device Configuration (top-right panel)*: A “Add Device” group allows selection of automatically generated name, type (sensor/gateway), body region, and transmission power before adding the device. All devices appear in a table listing ID, name, type, 3-D position, power, status, and edit/remove actions. Editing opens a modal dialog to modify those properties.

3) *Results Metrics (bottom-right panel)*:

- Organized into tabs:
 - Network Metrics – Summary table with key figures and recommendations.
 - Individual Links – Detailed link data (distance, path loss, received power).
 - Graphs – Plots of received power, distances, channel capacity.
 - Algorithm Comparison – Compare PSO, GA, etc., with convergence curves and metric tables.
 - Weight Configuration – Choose fitness strategies and set component weights.
 - Propagation Settings – Pick predefined profiles or fine-tune model parameters.
 - Detailed Report – Full textual report of optimization outcomes.

B. 3-D Rendering Component

The 3-D Rendering component is responsible for loading (in format .obj) and rendering 3-D models. It uses the Trimesh library [8] for geometric processing and OpenGL for real-time rendering [9]. The model enables placement of devices on the body surface (green ball is BNC and red is a sensor) and verification of Line-of-Sight (LoS) conditions between devices using ray-casting on different 3-D models (any posture can evaluate). As shown in Fig.2.

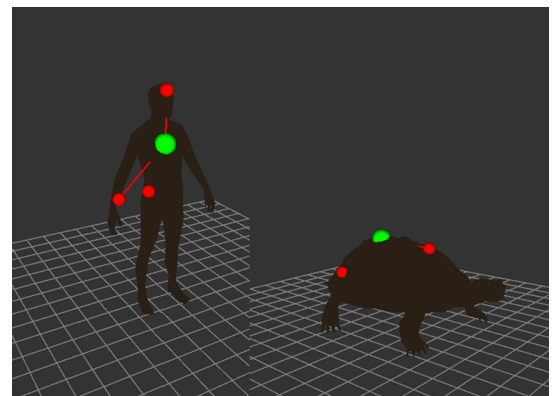


Fig. 2: Example loaded 3D models.

C. Propagation Calculation Component

This component implements the IEEE 802.15.6 standard model [2] and provides methods to compute path-loss, received power and link margin between devices.

The coefficients presented in this document are specifically derived for on-body propagation scenarios, which represent the most common deployment environment for WBAN applications. In on-body scenarios, both the transmitter and receiver devices are placed directly on or very close to the human body surface, the physical-layer parameters are customizable through a GUI, as shown in Fig. 3.

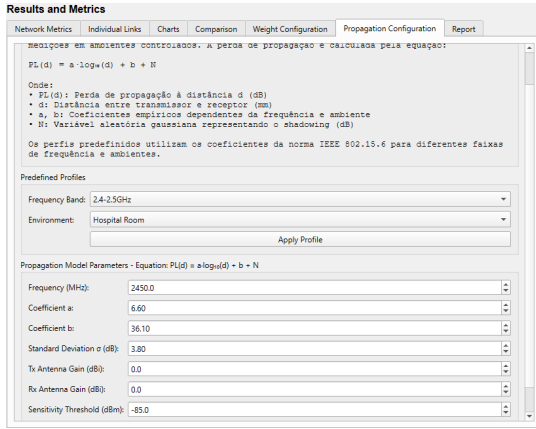


Fig. 3: Configurable physical layer parameters.

1) *Path-Loss Model*: The IEEE 802.15.6 standard employs a logarithmic path-loss model to describe the wireless channel in a WBAN, given by

$$PL(d) = a \log_{10}(d) + b + N \quad (1)$$

where $PL(d)$ (dB) represents the path loss at distance d (mm); a and b are coefficients that depend on the frequency band and the environment; and $N \sim \mathcal{N}(0, \sigma^2)$ is a zero-mean Gaussian random variable that models the shadowing effect.

2) *Model Parameters*: Model parameters vary according to the channel scenario, as shown in Table I. The coefficients provided in the accompanying tables are optimized for the on-body scenario, which is the focus of most WBAN applications in healthcare monitoring. These coefficients account for the specific electromagnetic properties of the human body surface and the typical distances between sensors in medical applications.

3) *Received Power Calculation*: The received power is obtained by accounting for the gains of the transmitting and receiving antennas, as expressed in Eq. (2):

$$P_{rx} = P_{tx} - PL(d) + G_t + G_r \quad (2)$$

where P_{rx} (dBm) denotes the received power, P_{tx} (dBm) the transmit power, G_t (dBi) the gain of the transmitting antenna, and G_r (dBi) the gain of the receiving antenna.

D. Optimization Component

The optimization component implements two meta-heuristic algorithms: PSO, GA. Each algorithm is configurable via specific parameters and can be used to simultaneously optimize

TABLE I: IEEE 802.15.6 propagation model coefficients for different frequency bands and environments.

Freq. Band	Environment	Coeff. a, b	Std. dev. σ
400-450 MHz	Hospital Room	3.00, 34.60	4.63
	Anechoic Chamber	22.60, -7.85	5.60
608-614 MHz	Hospital Room	16.70, -0.45	5.99
	Anechoic Chamber	17.20, 1.61	6.96
950-956 MHz	Hospital Room	15.50, 5.38	5.35
	Anechoic Chamber	28.80, -23.50	11.70
2.4-2.5 GHz	Hospital Room	6.60, 36.10	3.80
	Anechoic Chamber	29.30, -16.80	6.89
3.1-10.6 GHz	Hospital Room	19.20, 3.38	4.40
	Anechoic Chamber	34.10, -31.40	4.85

BNC placement and sensor transmission powers. As shown in Fig. 4.

1) *Particle Swarm Optimization (PSO)*: PSO is an optimization algorithm inspired by the collective behaviour of bird flocks; each particle represents a candidate solution and moves in the search space according to its own best position and the best position found by the whole swarm [10].

2) *Genetic Algorithm (GA)*: The genetic algorithm is an optimization method based on the principles of natural evolution. It employs selection, crossover and mutation operators to evolve a population of candidate solutions over successive generations [11].

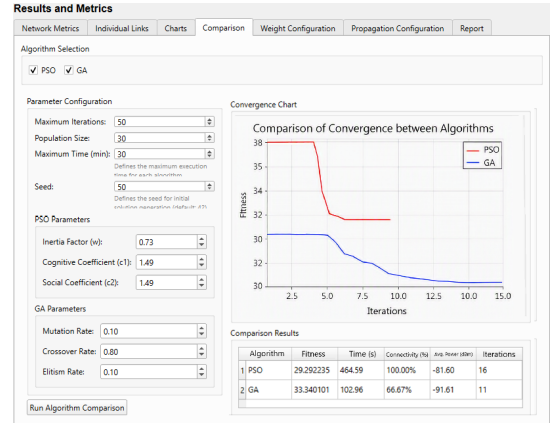


Fig. 4: GUI for optimization (configuration and results).

3) *Fitness Function*: The framework employs a multi-objective fitness function that aggregates several network performance metrics, as shown in Eq. (3):

$$F = w_c (1 - C) + w_p (1 - P_{\text{norm}}) + w_b \text{Var}_{p_{\text{norm}}} + w_d D_{\text{norm}} + w_e E_{\text{norm}} + w_i \text{Var}_{\text{ratio}_{\text{norm}}} \quad (3)$$

In this expression C is the connectivity rate, P_{norm} the normalized received power, $\text{Var}_{p_{\text{norm}}}$ the variance of the normalized powers, D_{norm} the normalized total inter-node distance, E_{norm} the normalized energy consumption, and $\text{Var}_{\text{ratio}_{\text{norm}}}$ the variance of the distance-to-power ratio; each term is weighted by a configurable coefficient $w_c, w_p, w_b, w_d, w_e, w_i$, as show in Fig. 5. The algorithm (PSO or GA) aim to *minimize* F , each term

contributes a penalty that is reduced when the corresponding performance metric improves.

All terms are normalised to $[0, 1]$ and the non-negative scalar weights $w_c, w_p, w_b, w_d, w_e, w_i$ let the designer steer the search toward the most relevant performance aspects.

- Connectivity ($C \in [0, 1]$) – fraction of nodes that can reach at least one gateway (penalised by $1 - C$).
- Mean received power (P_{norm}) – normalised average power; low values penalised by $1 - P_{\text{norm}}$.
- Power uniformity ($\text{Var}_{P_{\text{norm}}}$) – variance of normalised powers; minimisation yields homogeneous links.
- Inter-node distance (D_{norm}) – normalised sum (or mean) of sensor-to-gateway Euclidean distances; smaller values reduce required transmit power.
- Energy consumption (E_{norm}) – normalised total sensor energy per episode; directly penalised.
- Distance/power balance (d/p) and its normalised variance $\text{Var}_{\text{ratio}_{\text{norm}}}$; minimising the variance avoids a few nodes compensating long hops with high power.

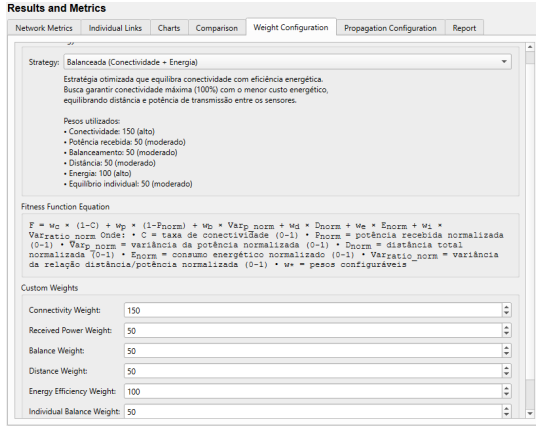


Fig. 5: Customizable weights for the fitness function.

Weight interpretation:

- $w_c \uparrow$ – enforce full connectivity (safety-critical);
- $w_e, w_d \uparrow$ – favour low-energy topologies;
- $w_b, w_i \uparrow$ – promote uniform link quality;
- $w_p \uparrow$ – guarantee SNR margin (reliability vs. power).

III. RESULTS AND DISCUSSION

The framework's outputs are designed to support multiple use cases, from academic research in wireless communication to industrial development of medical wearable devices. The comprehensive metrics and visualization tools facilitate both quantitative analysis and intuitive understanding of network behavior.

A. Network Metrics

The main metrics of the WBAN are fundamental parameters that allow evaluating the performance and quality of communication between sensor devices and the central gateway. These metrics are calculated based on the IEEE 802.15.6 propagation model, which considers the specific communication conditions

on body environments. The Fig. 6 shows results for metrics calculated after optimization, such as:

- Total Number of Sensors: Complete count of active sensor devices in the WBAN network. *Unit:* devices
- Connected Sensors: Number of sensors that established an effective connection with the gateway. *Unit:* devices
- Connectivity Rate: Percentage proportion of connected sensors relative to the total number of sensors. *Unit:* %
- Network Coverage: Proportion of body area effectively monitored by the network. *Unit:* %
- LoS Sensors: Number of sensors with a direct line-of-sight to the gateway. *Unit:* devices
- NLoS Sensors: Number of sensors without a direct line-of-sight to the gateway. *Unit:* devices
- LoS Rate: Percentage proportion of sensors enjoying favourable propagation conditions (i.e., LoS). *Unit:* %
- Average Obstruction: Average percentage of interference (obstruction) in the signal paths. *Unit:* %
- Average Path Loss: Mean signal attenuation along the communication links. *Unit:* dB
- Average Received Power: Mean power received by all sensors in the network. *Unit:* dBm
- Minimum Received Power: Lowest received power value recorded in the network. *Unit:* dBm
- Maximum Received Power: Highest received power value recorded in the network. *Unit:* dBm

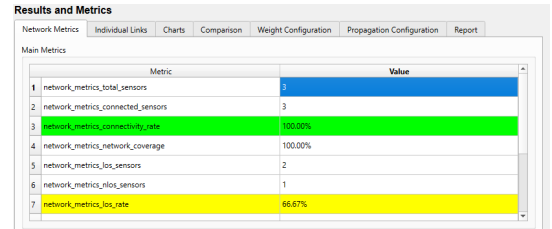


Fig. 6: Network metrics.

B. Visualization

The framework supplies three concise graphical views, shows in Fig. 7:



Fig. 7: Visualization of WBAN performance optimization.

- 1) Received Power: colour-coded bars per sensor (green $> P_{\text{sense}}$, red $< P_{\text{sense}}$) with a reference line at P_{sense} .
- 2) Distance: bar plot of d_i (sensor–gateway) to spot outliers and assess distance–quality correlation.
- 3) Channel Capacity: bar plot of C_i for bandwidth and bottleneck analysis.

C. Convergence Analysis

The tool incorporates evaluation modules that allow a direct comparison of the solutions proposed by the PSO and GA. The metrics are:

- Fitness value: the objective function (or *cost*) obtained at the end of the optimization; the lower the value, the better the solution.
- Execution time: total execution time of the optimization (in seconds), measured from the start of the population generation until convergence or the termination of the maximum number of iterations.
- Number of iterations: number of iterations required for the algorithm to meet the stopping criterion (e.g., fitness variation below a given threshold).

To facilitate the analysis of the search dynamics, the framework generates, the convergence plot of both algorithms on the same axes, as show in Fig. 8, the x-axis represents the number of iterations, and the y-axis represents the fitness value (lower is better).

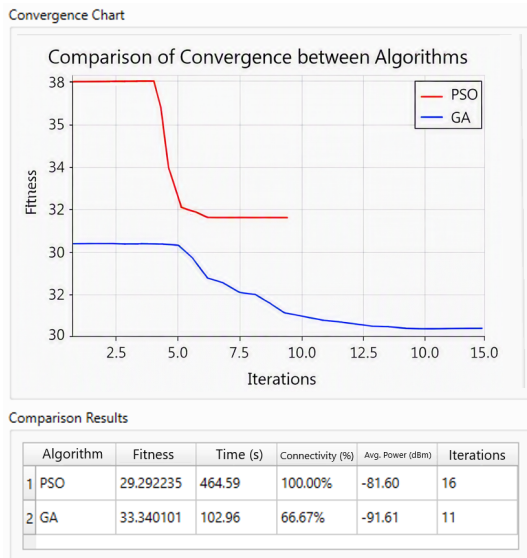


Fig. 8: Comparative metrics and convergence graph.

The interpretation of the results it is convergence speed refers to how quickly an algorithm attains a stable fitness value; the algorithm that does so in fewer iterations is generally the most efficient in terms of computational time. Solution quality considers that, although an algorithm may require more iterations, it can still produce a slightly better fitness, so the choice between methods depends on the trade-off between solution quality and computational cost.

Finally, stability is assessed by examining the fitness curves: strong oscillations indicate sensitivity to internal parameters

such as the inertia coefficients in PSO or the mutation rate in GA. Thus, the framework not only provides the final numerical results but also supplies visual tools that facilitate decision-making regarding which algorithm (or parameter combination) is best suited for the WBAN scenario under study.

IV. CONCLUSION

The WBAN coordinator placement framework provides a comprehensive suite of tools for analyzing and optimizing BNC placement. Its detailed outputs and intuitive visualizations enable deep understanding of network behavior across various scenarios, making it an indispensable tool for researchers, developers, and engineers working with many applications (Industrial Automation, Security/Surveillance and Healthcare).

The combination of quantitative metrics with graphical visualizations facilitates both technical analysis and communication of results to different stakeholders. The automatically generated reports save time in documentation and enable systematic comparative analysis between different approaches.

The framework's modular architecture and comprehensive feature set position it as a important tool in WBAN research and development.

Future developments could include integration with machine learning algorithms for predictive optimization, support for additional wireless standards, and enhanced visualization capabilities for virtual reality environments. The framework's solid foundation provides an excellent platform for these advanced features while maintaining its core functionality and usability.

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