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RESEARCH ARTICLE

# Optimal Wireless Sensor Networks Allocation for Wooded Areas Using Quantum-Behaved Swarm Optimization Algorithms

**WASHINGTON VELASQUEZ, (Senior Member, IEEE), FREDDY JIJON-VELIZ, AND MANUEL S. ALVAREZ-ALVARADO, (Member, IEEE)**
Faculty of Electrical and Computer Engineering, Escuela Superior Politécnica del Litoral, (ESPOL), Guayaquil 09-01-5863, Ecuador
Corresponding author: Washington Velasquez (wavelasq@espol.edu.ec)

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**ABSTRACT** This paper aims to present a robust algorithm developed that aims to minimize the number of sensor nodes in a WSN using three quantum-behaved swarm optimization techniques based on Lorentz (QPSO-LR), Rosen–Morse (QPSO-RM), and Coulomb-like Square Root (QPSO-CS) potential fields. The algorithm aims to allocate the minimum number of wireless sensors in forested areas without losing connectivity in an environment with a high penetration of vegetation. The proposed approach incorporates a propagation model that locates the sensor nodes, calculates the approximate separation distance between each one, verifies Line of Sight (LOS) compliance, and avoids considerable intrusions in the first Fresnel zone. The results validate the robustness of the quantum-behaved swarm optimization algorithms in comparison to traditional particle swarm optimization (PSO).

**INDEX TERMS** Network design, particle swarm optimization, quantum-behaved algorithms, wireless sensor network.

## NOMENCLATURE

| | |
|---|---|
| $\lambda$ | Wavelength. |
| $C$ | Cost Funtion. |
| $c$ | Cognitive Coefficient. |
| $d$ | Distance. |
| $d_f$ | The depth of foliage along the path. |
| $f$ | Transmission Frequency. |
| $G$ | Gain. |
| $g$ | Optima Global Position of the Swarm N. |
| $L$ | Path Loss. |
| $P$ | Power. |
| $q$ | Best Position. |
| $r$ | Vector of random values between 0-1. |
| $t$ | Time. |
| $u$ | Random number. |
| $V$ | Potencial Field. |
| $v$ | Particle Speed. |
| $w$ | Inercia Coefficient. |
| $X$ | Best Global Position. |
| $x$ | Position. |

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## I. INTRODUCTION

Information and Communication Technologies (ICTs) provide a variety of electronic devices and computer equipment capable of processing information and using it to control processes and predict/prevent disasters [1]. Due to issues related to global warming [2] or human incidence [3], there have been several emergencies worldwide, even with a contingency plan. The rulers of affected countries and districts seek ways to control or avoid wildfire or other disasters [4], [5]. However, the increase in the rate of wildfires is a global concern [6]. Wildfires are one of the problems that affect specific areas worldwide every year, e.g., the Australian fires in 2020 [7], when the extension of the forest burned exceeded everything observed until to date, or on August 25, 2019, when a large fire affected the border territory between Bolivia, Brazil, and Paraguay [8]. In a study by the World Wildlife Fund (WWF) and Boston Consulting Group (BCG) in April 2020, fire alarms increased by 13 % compared to 2019 [9]. Variations in the frequency, intensity, location, and severity produced mainly through human action, can affect the spontaneous creation of fires in unexpected areas. These cause severe impacts on the ecosystem and the loss of biodiversity, increase the capacity of greenhouse gases, and cause production problems in national economies [8].

Some studies focus on data fusion and processing wireless multimedia sensor networks with a view to reduce the amount of data to be transmitted over the network by intra-node processing [10], [11]. Some other studies focuses on the applications and mechanisms to create Wireless Sensor Networks (WSNs) [12], [13], [14], [15]; these allow for the protection and monitoring of areas in danger; however, the terrain's topography can affect a traditional design in the network. For this reason, the creation of WSNs, mainly in wooded or mountainous areas, must be accompanied by a specific study of where the WSN will be implemented, which affects implementation times with more significant human effort [16]. The implementations use specific ICTs because they are affected by terrain [17], antenna, propagation model [18], and others. In addition, specific optimization algorithms are used to improve some WSN characteristics, e.g., the location of the antennas (nodes) using Particle Swarm Optimization (PSO) [19]. However, these traditional algorithms may take time to process all the information depending on the expansion area of the WSN and other environment variables.

The main contribution of this work is a novel algorithm with low computational burden that deals with the optimal location sensor nodes in a WSN, considering a forested area with high penetration of vegetation (realistic model). The optimization is performed using three quantum-behaved swarm optimization algorithms (QPSO) that employ quantum physics resulting in a robust optimization technique. The proposed approach incorporates terrain topology, line of sight between sensor nodes, propagation models, link gain, Fresnel radius, transmitter and receiver power, and path loss caused by the environment.

The remainder of this paper is composed of six sections. Section II describes the motivation and literature review according to propagation models, WSNs, and optimization algorithms. Section III introduces the methodology for the design of the WSN, indicating the interaction between the propagation algorithm and optimization algorithms. Section IV presents the simulation environment for validating the method with the proposed scenarios. Section V presents the analysis of the results of the scenarios and the behavior of the optimization algorithms. Finally, some conclusions about the different designs and optimization algorithms are indicated in section six.

## II. BACKGROUND AND LITERATURE REVIEW

This paper is the continuation of previous works that describe the preliminary development of an application that allows combating problems related to spreading forest fires and monitoring outdoor areas using sensors. Reference [20] describes the simulation tool for spreading forest fires, developed using transition rules in cellular automata, considering density and type of vegetation, wind speed and direction, and terrain elevation, among other parameters. On the other hand, [21] describes a prototype for the dynamic creation of evacuation routes in forest fires using a virtual sensor network (VSN) that obtains data on temperature, humidity, atmospheric pressure, wind speed, and other parameters received from a web weather API. These are set up into a forest fire propagation algorithm with an initial coordinate (latitude, longitude) to start the simulation and predict how the disaster will spread. The algorithm allows the creation of a safe evacuation route that changes depending on the evolution of the propagation algorithm; the information would be valuable in case of evacuation of people or animals in danger. However, the sensor network only considered the distance between the antennas, not the elevation and the line of sight between them. In the present work, we seek to provide a solution to the VSN problems in such a way as to ensure communication in sensor nodes using propagation models in forested scenarios to calculate path loss. In addition to obtaining a line of sight between the points using data from Google Maps, considering the Fresnel radius and optimizing the sensors' location, using meta-heuristic algorithms to distribute them over the area according to the elevation of the terrain and other parameters. Finally, These designs may vary according to the WSN monitoring area, so the aim is to improve the server's processing times using the QPSO algorithms instead of PSO.

### A. PARTICLE SWARM OPTIMIZATION

Particle swarm optimization (PSO) is a heuristic optimization method it seeks to find the minimum or maximum value according to an objective function. It works by imitating the behavior of animal communities such as Herds/Flocks. The units of these sets are known as particles and have the following characteristics:

- *Position:* Current location of the particle.
- *Cost:* Value of the position evaluated in the cost function.
- *Velocity:* Indicates where the particle is moving.
- *New position*: Best position of a particle so far found

The particles are evaluated in a cost function or objective function. After the new position is updated, if it is a local maximum or minimum, the termination criterion is validated; if it is not met, the process is repeated to search for a new local maximum or minimum.

A particle's motion is given by eqn. (1):

$$v_i(t+1) = wv_i(t) + c_1r_1[X_i(t) - x_i(t)] + c_2r_2[g(t) - x_i(t)] \quad (1)$$

where,

- $v_i(t+1)$: Particle speed $(i)$ at the moment $(t+1)$.
- $v_i$: Particle speed $(i)$ at time $(t)$
- $w$: Inertia
- $c_1$: Cognitive coefficient.
- $r_1$: Vector of random values between $0-1$.
- $X_i(t)$: Best global position of the particle.
- $x_i(t)$: Position of the particle $(i)$ at time $t$.
- $c_2$: Social coefficient
- $r_2$: Vector of random values between $0-1$.
- $g(t)$: Swarm position at time $t$.

After calculating the velocity, we proceed to update the particle's position. Equation (2) is used for this purpose.

$$x_i(t+1) = x_i(t) + v_i(t+1) \quad (2)$$

**TABLE 1.** z Function for different bounded potential fields taken form [22].

| Potential field | z function |
|---|---|
| Lorentz (QPSO-LR) | $\left\lvert x_l^{(k)} - \frac{1}{N}\sum_{l=1}^{N} q_l^{(k)}\right\rvert \sqrt{\frac{1-u}{u}}$ |
| Rosen–Morse (QPSO-RM) | $\left\lvert x_l^{(k)} - \frac{1}{N}\sum_{l=1}^{N} q_l^{(k)}\right\rvert sech^{-1}(\sqrt{u})$ |
| Coulomb-like Square Root (QPSO-CS) | $\left\lvert x_l^{(k)} - \frac{1}{N}\sum_{l=1}^{N} q_l^{(k)}\right\rvert (ln(\frac{1}{u}))^{2/3}$ |

The equation (3) is used to prevent the algorithm from taking excessive speeds. The possible positions have been limited in a range according to the area chosen by the user. If any variable exceeds the limits, it is changed to the limiting value, and its speed is automatically set to zero.

$$vmax = k(xmax - xmin)/2; \tag{3}$$

Then, a linear decrease of the inertia coefficient is performed to favor the convergence of the particles, depending on the number of iterations. As indicated in the eqn. (4).

$$wt = (w_{max} - w_{min})(\frac{t_{max} - t}{t_{max}}) + w_{min} \tag{4}$$

where, $wt$ is the inertia coefficient in the current iteration ($t$), $w_{max}$ is the maximum inertia coefficient, $w_{min}$ is the minimum inertia coefficient, and $t_{max}$ is the number of total Iterations.

## B. QUANTUM PARTICLE SWARM OPTIMIZATION

Quantum Particle Swarm Optimization (QPSO) is a meta-heuristic optimization technique that in contrast with traditional PSO, it employs quantum theory to describe the movement of a quantum particle as evidenced in [22]. Moreover, there is evidence about the efficacy of QPSO in the field of system reliability [23], [24] and maintenance planning. Focusing on the mathematical formulations that describe the optimization technique, authors in [22] determined that the actual position $x$ of the particle $l$ at iteration $k$ can be described as given in eqn. (5), where $z$ represents the displacement of a particle that depends on the actual position of the particle and the bounded potential field $V$ that excites the movement of the particle; the term $u$ represents a random number that avoids local optima, while $w$ is the acceleration factor such that $0 \leq w \leq 2$; the local best position is by $q$ and the optima global position of the swarm $N$ is represented by $g$.

$$\begin{aligned} x_l^{(k+1)} &= z(x_l^{(k)}, V) + D_l^{(k)} \\ D_l^{(k)} &= ((w_1u_1)/(w_1u_1 + w_2u_2))q_l^{(k)} \\ &\quad +(1 - (w_1u_1)/(w_1u_1 + w_2u_2))g^{(k)} \end{aligned} \tag{5}$$

In this paper, apart from traditional PSO, three quantum-behaved swarm optimization algorithms based on Lorentz (QPSO-LR), Rosen–Morse (QPSO-RM) and Coulomb-like Square Root (QPSO-CS) potential fields are employed. For every potential field there is a different $z$ function, which mathematically are described in Table 1 [22], which are the key drivers in this research.

## C. WIRELESS SENSOR NETWORK

Wireless sensor networks (WSN) offer a resource-limited environment control solution. Optimizing operating resources is essential for the efficient use of electronic devices. Research on the coexistence of networks or their optimization is a varied field, and they provide possible solutions, e.g., [25] analyzes the coexistence of the WSN with Software Defined Networks (SDN) to increase the network's processing capacity and the efficiency of its resources. The optimization strategies even reach the issue of power in the WSN. PSO is a known method based on a population of particles that move a defined area to find the best local and global positions. There are several works where PSO has been used in WSN, e.g., [26] applies PSO in a distance-vector jump location algorithm to minimize the problems of locating nodes in a WSN in parameters such as the number of errors, error variation, and positioning precision. The localization of nodes in a WSN can be decreased in accuracy by the nonline of sight (NLOS) in [27] uses of the Kalman filter algorithm to reduce the NLOS error, combined with the least-squares method and with PSO to estimate the location of nodes in a WSN.

Energy-efficient routing problems also be solved with metaheuristic methods, e.g., [28] describes a dynamic clustering and processing protocol based on multi-objective particle swarm optimization with the Levy distribution algorithm (MOPSO-L). Reference [29] seeks to make an energy-efficient algorithm for software-defined wireless sensor networks (SD-WSN), with the premise that these systems can be configured after implementation. This paper proposes a routing algorithm where PSO was used to minimize the transmission distance, optimize the network's energy consumption, and prolong the devices' useful life.

Finally, it is possible to formulate mathematical expressions to develop meta-heuristic search optimization algorithms based on the behavior of the quantum particles. It was designed with some quantum-inspired algorithms, which scenario is a particle swarm that is excited by Lorentz, Rosen–Morse, and Coulomb-like square root potential fields. The mathematical model and the validation scenarios to solve 24 benchmark functions categorized by uni-modal, multi-modal, and fixed-dimension multi-modal are described in detail in [22]. This paper will use quantum-inspired algorithms to design a wireless sensor network and compare it with a classical algorithm (PSO).

## D. WSN PROPAGATION MODELS

Electronic devices and their exponential growth have already led to the use and analysis of vegetation propagation models in different environments, e.g., [30] describes signal loss models in urban environments, closed spaces as rooms, and open spaces; for example, the building's roof. These documents are helpful for studies based on urban or suburban locations but not for forest environments. A comparison of their results and formulations is made in [31]; this article analyzes the current development in this field, reviewing propagation models and evaluating their empirical data, mentioning that the Weissberger model is optimistic compared to the

ITU model. The environment limits the application of these models, which is why [32] methods are proposed to evaluate the attenuation and range of electromagnetic waves on roads that pass through wooded areas. In this case, the Weissberger model had a poor approximation of the loss values, given that it was not made in this environment. Finally, [33] describes the uses of the Weissberger propagation model to approximate the energy a node will consume in a WSN to propose a transmission power control algorithm. They show the graph of energy consumed vs. distance, indicating power savings. A better life for the nodes is obtained with the Weissberger model, which makes sense; knowing that the model is optimistic, it will have fewer losses, therefore, less consumption. Specific criteria taken into account in the propagation model are described below.

#### 1) INSERTION LOSS

The insertion loss in a path is the ratio of the transmitted power to the received power. Loss is an additional value. In addition, other elements that cause interactions on the propagation wave are considered; in this case, cable losses will be neglected. The insertion loss is given by eqn. (6):

$$L(dB) = P_T(dB) + G_T(dB) + G_R(dB) - P_R(dB) \tag{6}$$

where, $P_T$ is transmission power, $G_T$ is the gain of the transmitting antenna, $G_R$ is the gain of the receiving antenna, and $P_R$ is the power received by the antenna.

#### 2) PROPAGATION MODELS

Propagation models are divided into empirical, semi-empirical, and analytical models. Empirical models perform accurate field measurements and interpolation methods; the semi-empirical models use a double slope attenuation function, describing the coherent and the incoherent component. Analytical models are based on statistical theory and are used to model the confusing element in the spectrum [34].

##### *a: FREE SPACE PATH LOSS (FSPL)*

FSPL is the power attenuation between two antennas in area obstacle free and with line of sight.

For this scenario, the calculations with empirical models will be used. The Friis Free Space model is defined by the eqn. (7):

$$L_o(dB) = -20\log\left(\frac{\lambda}{4\pi d}\right) \tag{7}$$

where, $\lambda$ is the wavelength and $d$ is the distance between the antennas (measured in meters).

Finally, solving for d:

$$d = \frac{\lambda}{4\pi\, 10^{\frac{L_o}{-20}}} \tag{8}$$

##### *b: WEISSBERGER'S MODEL (WEISS)*

WEISS approximates losses in dense, dry, and leafy forest environments. The equation (9) describes the model for predictions between the bands from *230 MHz* to *95 GHz*.

$$L(dB) = \begin{cases} L_o + 0.45\, f^{0,284} d_f & d_f < 14m \\ L_o + 1.33\, f^{0,284} d_f^{0.588} & d_f > 14m \end{cases} \tag{9}$$

where, $d_f$ is the Foliage Depth in meters and $f$ is the link frequency in GHz.

Finally, solving for d:

$$d = \begin{cases} \dfrac{\lambda}{4\pi\, 10^{\frac{L-0.45\, f^{0,284} d_f}{-20}}} & d_f < 14m \\ \dfrac{\lambda}{4\pi\, 10^{\frac{L-1.33\, f^{0,284} d_f^{0.588}}{-20}}} & d_f > 14m \end{cases} \tag{10}$$

##### *c: ITU EARLY VEGETATION MODEL*

This model was developed for the VHF and UHF band *(< 400m)*; however, it is usually used for bands between *200 MHz* and *95 GHz*. Only the components diffracted from the top, from the ground, and around the vegetation are estimated in the model. The model is defined by eqn. (11).

$$L(dB) = L_o + 0.2\, f^{0,3} d_f^{0.6} \tag{11}$$

where, $d_f$ is the Foliage Depth in meters and $f$ is the link frequency in MHz.

Finally, solving for d:

$$d = \frac{\lambda}{4\pi\, 10^{\frac{L-0.2\, f^{0,3} d_f^{0.6}}{-20}}} \tag{12}$$

### *E. RELATED WORKS*

The monitoring platforms are commonly used to view the location and network data. The platforms used in sensor networks are not innovative; they are widely used commercially in different applications, for example, "GPS Trackers." There are works on web pages or platforms that can be used to create or monitor WSN, e.g., in [35], a platform for monitoring vibration screen ligaments was developed and designed to operate in industrial and harsh environments. It introduced a new approach to WSNs as it was based on an ARM Cortex M3 architecture, rendering other architectures obsolete. Reference [36] details a functional design and implementation of a WSN platform for long-term, low-cost IoT environmental monitoring applications. It covers the practical development, from scratch, of a complete WSN platform. Consider aspects such as flexibility, reuse components, sensor and gateway node optimization, communication protocols, and error correction. The platform demonstrates quite a bit of flexibility because the components are used in a wide range of indoor and outdoor deployments. In these two articles, we talk about monitoring platforms. However, some platforms seek to facilitate design, as in [37], a work where a WSN platform for design is developed, only a diagram of the architecture is made, to then automatically generate the firmware for the micro-controllers and the wired network. The Web platform supports many sensors and micro-controllers, plus users can add their components.

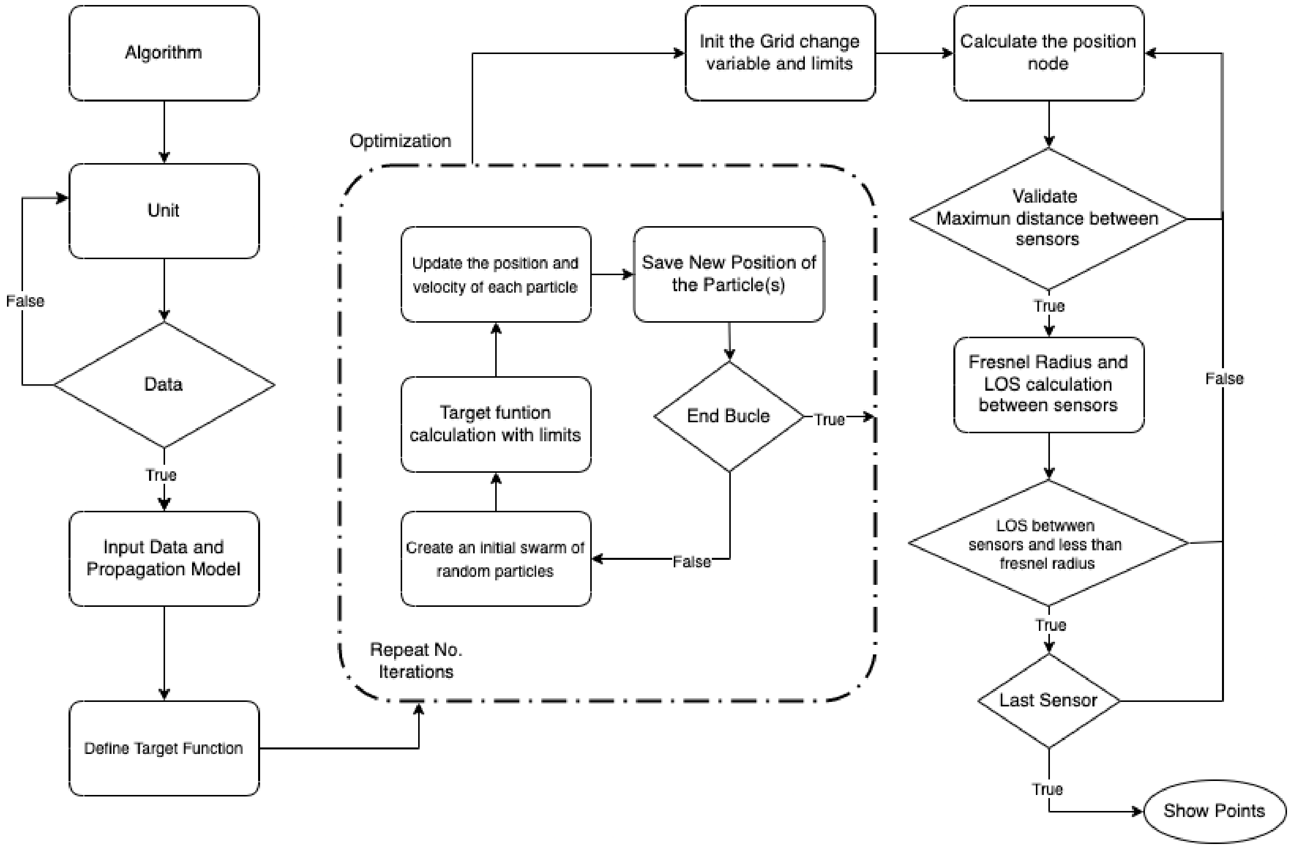



**FIGURE 1.** Flow diagram of the interaction of the propagation algorithm with the optimization algorithm.

Finally, in the current literature, no application automatically delivers the physical positions of the sensor nodes in a WSN according to the user's input parameters (antennas, propagation, network area) and considers factors such as terrain elevation and losses between the nodes. Also, consider metrics to reduce the number of nodes covering a forested area, using quantum-inspired swarm optimization algorithms to find the best geographic coordinates for node communication.

## III. METHODOLOGY

This section describes the methodology used for the wireless sensor network design with different wave propagation models in forest environments and the optimization algorithms with a specific cost function.

Figure 1 indicates the interaction flowchart of the propagation and optimization algorithms. The user selects the expansion area to create the WSN and the frequency and propagation model to keep the antennas' transmit and receive power values constant. The optimization algorithm complements the wave propagation algorithm to improve the location and number of nodes in the WSN.

### A. PROPAGATION ALGORITHM

The objective of this algorithm is to calculate the maximum distance between one point and another in the mesh, according to the Free Space, Weissberger, ITU propagation model, and the initial parameters indicated by the user (antenna power). The calculations are made to obtain the path losses taking into account the characteristics of the antennas using eqn. (6). Then, the maximum transmission distance is obtained using equations (8), (10), and (12), depending on the values obtained by the loss functions of the transmission model propagation chosen by the user. Finally, four locations are received in latitude and longitude geographic coordinate format, and a quadrilateral is formed with these points. Each point symbolizes a corner in the quadrilateral *[A, B, C, D]* as shown in figure 2, and the coordinates are converted to meters using the Google Mercator function for propagation calculations.

The limits for each sensor are created depending on the antennas' maximum distance and the terrain's topography. At the end of the iterations, the grids are obtained; each one will contain a network sensor, as shown in figure 3. Finally, the node will be located in the center of the mesh. If the terrain does not comply with the fresnel radius or there is no line of sight, a higher elevation area will seek to locate the antenna within limits as described in algorithm 1. The optimization algorithm will calculate the number of nodes for the case and the parameters entered by the user.

### B. COST FUNCTION: GOAL TO OPTIMIZE

The cost function to be optimized is the square of the ratio between the area of the geometric figure formed by the points *[A, B, C, D]* and the maximum distance between the antennas. The cost function gives the number of nodes about the user's initial values, as indicated in eqn. (14). The maximum

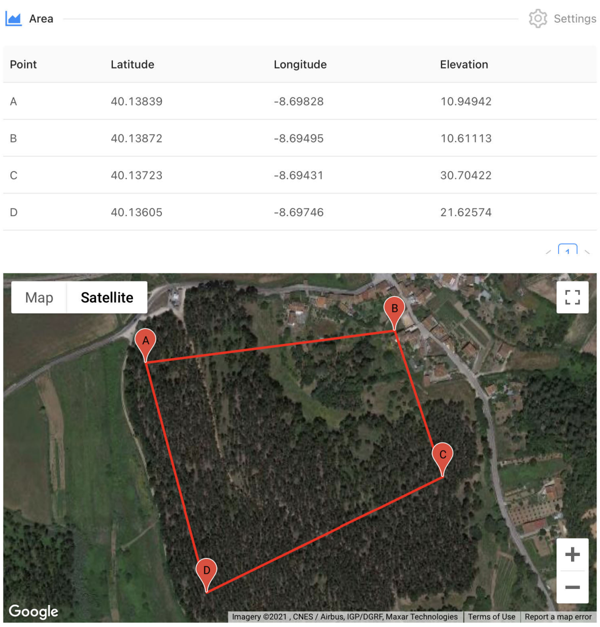



**FIGURE 2.** Area selection for the design of a wireless sensor network.

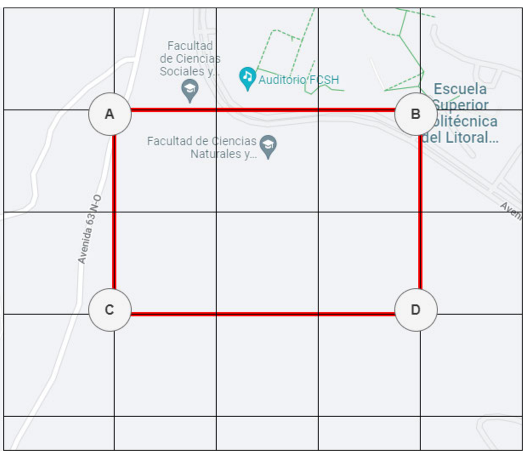



**FIGURE 3.** Wireless sensor network mesh.

distance ($D_{max}$) between the antennas is calculated using the *10 dB* link margin; subtracting the loss value without the margin gives the lower limit, and adding the upper margin gives the upper limit.

Mathematically, $D_{max}$ depends on the evaluation case, and it is expressed as follows:

$$D_{max} = \begin{cases} FSPL, & D_{max} -> eqn.(8) \\ WEISS, & D_{max} -> eqn.(10) \\ ITU, & D_{max} -> eqn.(12) \end{cases} \quad (13)$$

Finally, the cost function to maximize the $D_{max}$ in order to minimize the number of sensor node to implement in an area, we have:

$$C(D_{max}) = (Area/D_{max})^2 \quad (14)$$

where, $C(D_{max})$ is the cost function. *Area* represents the study surface. $D_{max}$ is the maximum separation distance between the nodes, which can vary depending on the link margin. $dF1(LdB)$ is the distance obtained with only path loss. $dF2(LdB+10dB)$ is the distance obtained with path loss and a link margin of *10dB*.

**Algorithm 1** Process of Propagations Wave's

**Result:** Point List
**Input:** Boundary Area (Lat,Lon), Antenna Transmission Power, Antenna Reception Power, Antenna Transmission Gain, Antenna Reception Gain, Propagation Model (FreeSpace, Weissberger, ITU).
**Output:** Node Position
It is calculated from the estimated path loss **(Lpath)**
The minimum distance is calculated **(DistanceAntennas)** (eqn. (3))
The points are arranged in a specific order to obtain the area. **(sorted_points)**
GoogleMercatorLatLonToMeters(sorted_points)
Initialization of variables of a Small Area.
Optimization Algorithm is run for this location (No_Particle, No_Variable, Limits)
**for** *columns* **do**
    The maximum and minimum location value for each sensor is defined.
    **for** *rows* **do**
        Line of Sight and Fresnel Radius Verification
        **if** *distanceArea < SumDistanceRow* **then**
            Next Column
        **else**
        **end**
    **end**
**end**

## C. OPTIMIZATION ALGORITHM

The determination of the minimum number of nodes n to place the wireless sensor networks in the mesh can be formulated as an optimization problem, which objective function is as follows:

$$min(C(D_{max})) = min((Area/D_{max})^2) \quad (15)$$

Subject to restrictions declared in eqn. (13).

In algorithm 2, the process of the optimization algorithm is presented. The swarm of particles is created, indicating parameters such as the number of particles, number of variables, and limits (maximum and minimum); each particle begins to be evaluated according to the cost function. When the particle changes position, its calculated parameters get closer to the optimal value sought. Finally, it obtains a list with the coordinates of each sensor in a network that ensures (by topographical and propagation criteria) the wireless connection between the nodes.

# IV. SIMULATION ENVIRONMENT

The methodology's validation is carried out by studying a specific area of the *Prosperina Protected Forest, Gustavo Galindo Campus, Guayaquil, Ecuador.* Table 2 shows the

**Algorithm 2** Optimization's Process

**Result:** Post position
**Input:** No_particle, No_variable, Limits.
**Output:** PositionSensor.
The Cost function is defined.
Swarm creation with N particles
**for** *Number of Iterations* **do**
  Cost function is evaluated
  The local attractor, cost and position of the particle are updated in the function
  Returns the values that minimize the function
  The number of Nodes is cleared.
**end**

**TABLE 2.** Values of the Xbee-Pro S2 model for sensor node communication.

| Antenna | GAIN (dBi) | TX PW (dBm) | TH PW (dBm) |
|---|---|---|---|
| Monopole | 1.5 | 10 | -102 |
| Dipole | 2.1 | 10 | -102 |
| Omni | 3.0 | 10 | -102 |

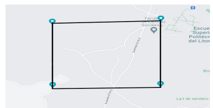
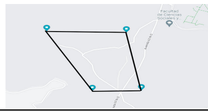
values set by default to the algorithm because each sensor node for communication depends on technology; in this case, the XBee-PRO S2 sensor with ZigBee technology is used in the range of 2.4GHz frequencies (node signal propagation).

The algorithms were programmed in Python and executed using an *Intel(R) Core(TM) i3-10110U* processor with a frequency of *2.10 GHz*, *8GB of RAM* and a *237 GB SSD* disk.

### A. CASE STUDY

Three scenarios were chosen randomly and evaluated with each optimization algorithm using an omni-directional antenna as transmitter and receiver. Table 3 shows the coordinates of each point of the quadrilateral for each case and shows the areas where the sensor network will be created.

**TABLE 3.** Different areas to evaluate optimization algorithms.

| # | A. ($m^2$) | P | Coordinate | Map |
|---|---|---|---|---|
| 1 | 849,120.68 | A<br>B<br>C<br>D | (-2.146729,-79.976833)<br>(-2.146358,-79.968057)<br>(-2.154464,-79.976801)<br>(-2.154347,-79.968078) |  |
| 2 | 303,749.56 | A<br>B<br>C<br>D | (-2.148206,-79.976809)<br>(-2.148348,-79.971493)<br>(-2.154100,-79.973753)<br>(-2.154020,-79.970493) |  |
| 3 | 154,559.51 | A<br>B<br>C<br>D | (-2.147735,-79.973253)<br>(-2.148417,-79.969130)<br>(-2.150099,-79.974462)<br>(-2.151176,-79.969229) |  |

Note: Area (A); Point (P)

## V. ANALYSIS OF RESULTS

This section presents the analysis of results and the behavior/evaluation of optimization algorithms using Big O notation.

### A. RESULTS OF THE PROPOSED SCENARIOS

The scenarios in Table 3 are evaluated using the three propagation models (Free Space, Weissberger, and ITU). The location of the sensor nodes is optimized using three quantum behavior algorithms (QPSO-RM, QPSO-CS, and QPSO-LR) and are compared with traditional PSO. In order to validate the results, the optimization was performed using 10, 100, and 1000 particles.

The total number of simulations include (3x areas) * (4x algorithms) * (3 x particle models) = 36 scenarios, as shown in Table 4.

Figure 4 shows the WSNs with the QPSO-LR optimization algorithm. The geographical coordinates are similar in each scenario because the resulting graphs do not vary with the other algorithms, as shown in Table 4. In all cases, an increase in the optimization algorithms' execution time is observed without noticeable improvements in the distance or the number of nodes; This improvement is minimal since an amount $n$ of iterations is being applied for each test. PSO presents the highest execution time compared to the other algorithms, e.g., the case for ten particles presents times 1.5 to 2 times higher compared to quantum algorithms; For 100 particles, the relationship increases with time between 4 to 5 times more significant. However, the times decrease for 1000 particles, and the time is 3 to 4 times greater concerning quantum algorithms. This particularity is due to the convergence speed of PSO that is lower for all scenarios compared to quantum algorithms. Among the quantum algorithms, the one with the best time is QPSO-LR for 10 and 100 particles; for 1000 particles, it is surpassed by QPSO-RM; however, this algorithm tends to converge in a more significant number of iterations compared to the QPSO-LR algorithm.

On the other hand, the number of nodes does not vary by changing the optimization algorithm, indicating that all algorithms converge to a unique result. Each propagation model estimates the loss; this causes the propagation distance between each model and the number of nodes to change. Free Space is an ideal model, which makes the distance between the nodes more significant. Weissberger and the ITU vegetation model consider the additional losses due to vegetation; this means having smaller distances between antennas, consequently, more nodes.

### B. PERFORMANCE OF OPTIMIZATION ALGORITHMS

The execution time of the optimization algorithms depends on the study area and the number of particles used to perform the calculations. Table 4 shows that all the algorithms arrive at the same response for the location of the nodes (separation) and in Fig. 4 that the positions (longitude, latitude, and elevation) for all the algorithms are the same. However, the execution time is different for the scenarios.

Fig. 5 shows the performance of the optimization algorithms based on the execution time to reach the (complete) solution. Big O notation is used for a better understanding of performance, showing that the proposed algorithms follow complexity of the form O(logn). For all the scenarios, PSO presents the higher computational burden as it requires the

**TABLE 4.** Results of the optimization algorithms for the different cases.

| | | | | # Particles | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | 10 | | | 100 | | | 1000 | | |
| **Case** | **Model** | **Algorithm** | **Nodes** | **Distance (m)** | **Time (s)** | **Velocity (s/#rep)** | **Distance (m)** | **Time (s)** | **Velocity (s/#rep)** | **Distance (m)** | **Time (s)** | **Velocity (s/#rep)** |
| *1* | *Free space* | PSO | 24 | 186,7663511 | 6,42517256 | 0,006425173 | 185,2396139 | 55,0215 | 0,055022 | 185,0114736 | 636,829555 | 0,636830 |
| | | QPSO-RM | 24 | 185,0479228 | 4,04499721 | 0,004044997 | 185,0479227 | 12,4911 | 0,012491 | 185,0479228 | 187,567516 | 0,187568 |
| | | QPSO-CS | 24 | 185,0479228 | 3,74604177 | 0,003746042 | 185,0479227 | 15,1269 | 0,015127 | 185,0479228 | 205,284384 | 0,205284 |
| | | QPSO-LR | 24 | 185,0479228 | 3,15392732 | 0,003153927 | 185,0479228 | 14,7579 | 0,014758 | 185,0479228 | 198,812492 | 0,198812 |
| | *ITU* | PSO | 127 | 78,57879921 | 6,13210535 | 0,006132105 | 78,57879920 | 54,9158 | 0,054916 | 78,57879921 | 609,597121 | 0,609597 |
| | | QPSO-RM | 127 | 77,10330116 | 3,30852460 | 0,003308525 | 78,47779978 | 14,5600 | 0,014560 | 78,47779979 | 190,056217 | 0,190056 |
| | | QPSO-CS | 127 | 78,47779979 | 3,92339849 | 0,003923398 | 78,47779979 | 16,1718 | 0,016172 | 78,47779979 | 202,102502 | 0,202103 |
| | | QPSO-LR | 127 | 78,47779979 | 4,47325635 | 0,004473256 | 78,47779979 | 12,9044 | 0,012904 | 78,47779979 | 195,417256 | 0,195417 |
| | *Weissberger* | PSO | 86 | 100,9679709 | 5,92424869 | 0,005924249 | 100,9679709 | 52,4634 | 0,052463 | 100,9679709 | 624,420897 | 0,624421 |
| | | QPSO-RM | 86 | 99,19609879 | 3,62118649 | 0,003621186 | 100,9519182 | 12,5834 | 0,012583 | 100,9519183 | 188,817982 | 0,188818 |
| | | QPSO-CS | 86 | 100,9519183 | 3,34518528 | 0,003345185 | 100,3563265 | 13,4624 | 0,013462 | 100,9519183 | 200,186626 | 0,200187 |
| | | QPSO-LR | 86 | 100,3563265 | 3,25655436 | 0,003256554 | 100,9519182 | 13,2802 | 0,013280 | 100,9519183 | 191,185085 | 0,191185 |
| *2* | *Free space* | PSO | 7 | 186,766351 | 10,6010427 | 0,010601043 | 186,766351 | 53,3548870 | 0,053355 | 186,766351 | 639,397796 | 0,639398 |
| | | QPSO-RM | 7 | 189,446175 | 3,20532345 | 0,003205323 | 189,446175 | 13,8815760 | 0,013882 | 189,446175 | 190,173974 | 0,190174 |
| | | QPSO-CS | 7 | 182,554902 | 3,21187305 | 0,003211873 | 182,554902 | 15,8206763 | 0,015821 | 189,446175 | 207,531685 | 0,207532 |
| | | QPSO-LR | 7 | 182,554902 | 3,10788035 | 0,003107880 | 189,446175 | 14,6831297 | 0,014683 | 189,446175 | 196,031761 | 0,196032 |
| | *ITU* | PSO | 56 | 78,5787992 | 6,09401750 | 0,006094018 | 78,5787992 | 56,0669050 | 0,056067 | 78,5787992 | 633,922702 | 0,633923 |
| | | QPSO-RM | 56 | 75,8953223 | 3,21128654 | 0,003211287 | 78,3521147 | 14,0545783 | 0,014055 | 78,3521147 | 186,292769 | 0,186293 |
| | | QPSO-CS | 56 | 78,3521147 | 3,05904340 | 0,003059043 | 78,3521147 | 14,1693968 | 0,014169 | 78,3521147 | 191,967481 | 0,191967 |
| | | QPSO-LR | 56 | 78,3521147 | 3,11719393 | 0,003117194 | 78,3521147 | 14,1735165 | 0,014174 | 78,3521147 | 191,751214 | 0,191751 |
| | *Weissberger* | PSO | 31 | 100,967970 | 6,20939183 | 0,006209392 | 100,967970 | 50,7786829 | 0,050779 | 100,967970 | 640,828174 | 0,640828 |
| | | QPSO-RM | 31 | 97,5797001 | 3,16754317 | 0,003167543 | 100,711393 | 14,4078142 | 0,014408 | 100,711393 | 189,540420 | 0,189540 |
| | | QPSO-CS | 31 | 100,711393 | 2,98078680 | 0,002980787 | 100,711393 | 15,5691421 | 0,015569 | 100,711393 | 197,421591 | 0,197422 |
| | | QPSO-LR | 31 | 100,711393 | 3,17967271 | 0,003179673 | 100,711393 | 13,1886215 | 0,013189 | 100,711393 | 194,225785 | 0,194226 |
| *3* | *Free Space* | PSO | 6 | 182,612785 | 15,8645386 | 0,015864539 | 186,766351 | 140,035056 | 0,140035 | 182,036310 | 1510,49700 | 1,510497 |
| | | QPSO-RM | 6 | 186,173043 | 3,63859581 | 0,003638596 | 186,173043 | 12,5265610 | 0,012527 | 186,173043 | 120,089302 | 0,120089 |
| | | QPSO-CS | 6 | 186,173043 | 3,90334034 | 0,00390334 | 186,173043 | 13,4985082 | 0,013499 | 186,173043 | 154,111448 | 0,154111 |
| | | QPSO-LR | 6 | 186,173043 | 3,20307946 | 0,003203079 | 186,173043 | 13,0838003 | 0,013084 | 186,173043 | 149,599766 | 0,149600 |
| | *ITU* | PSO | 22 | 78,5787992 | 15,1436848 | 0,015143685 | 78,5787992 | 140,456555 | 0,140457 | 78,5787992 | 704,274980 | 0,704275 |
| | | QPSO-RM | 22 | 76,0048267 | 3,16504192 | 0,003165042 | 78,6724699 | 13,0935075 | 0,013094 | 78,6724699 | 179,109634 | 0,179110 |
| | | QPSO-CS | 22 | 78,6724699 | 3,79336476 | 0,003793365 | 78,6724699 | 16,1424508 | 0,016142 | 78,6724699 | 199,029112 | 0,199029 |
| | | QPSO-LR | 22 | 77,3041486 | 3,12684893 | 0,003126849 | 78,6724699 | 13,0947291 | 0,013095 | 78,6724699 | 193,567627 | 0,193568 |
| | *Weissberger* | PSO | 12 | 100,967970 | 14,7689781 | 0,014768978 | 100,967970 | 137,057260 | 0,137057 | 99,7090256 | 623,542076 | 0,623542 |
| | | QPSO-RM | 12 | 98,1218094 | 3,25473737 | 0,003254737 | 100,966508 | 13,3216159 | 0,013322 | 100,966508 | 190,986626 | 0,190987 |
| | | QPSO-CS | 12 | 100,966508 | 3,34843564 | 0,003348436 | 100,966508 | 13,3247799 | 0,013325 | 100,966508 | 206,854169 | 0,206854 |
| | | QPSO-LR | 12 | 100,966508 | 3,16187739 | 0,003161877 | 100,966508 | 12,9348323 | 0,012935 | 100,966508 | 194,247297 | 0,194247 |


**FIGURE 4.** **Wireless sensor network with QPSO-LR. a: Case 01, b: Case 02, c: Case 03.**

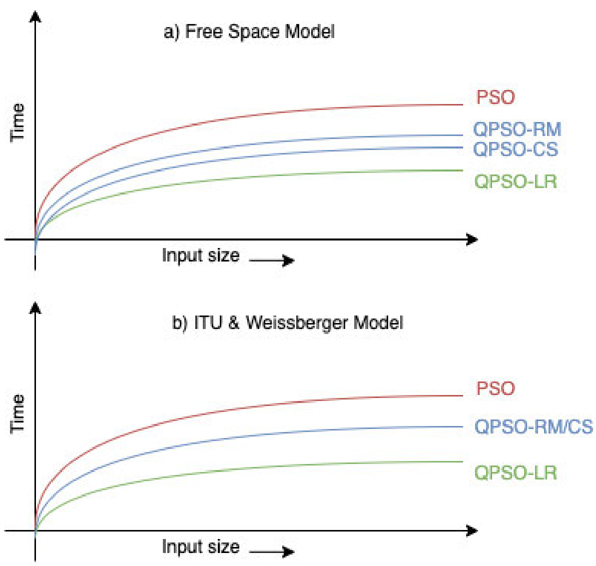



**FIGURE 5.** **Evaluation of algorithms using Big O notation. a) Free space model; b) ITU and Weissberger models.**

highest simulation time. QPSO-RM and QPSO-CS present similar performance, while QPSO-LR presents the fastest convergence for all scenarios, resulting in the best optimizer.

## VI. CONCLUSION AND FUTURE WORKS

This paper presents a mechanism capable of designing wireless sensor networks in forested areas, considering path losses in the environment and the terrain's topography. Three cases were analyzed by changing the study area, propagation model, optimization algorithm, and a different number of particles. Quantum particle swarm models (QPSO-LR, QPSO-RM, and QPSO-CS) have a shorter execution time than the traditional PSO algorithm, and their results converge to optimal values with fewer particles or iterations. QPSO-LR performs better than the other methods, with better results and a shorter convergence time. All optimization methods reach the same number of nodes, which validates the operation of each of the algorithms.

The propagation models for vegetation loss give an additional loss to the Free Space model. The Weissberger model has less loss than the ITU model, which is considered pessimistic. The Weissberger propagation model would better approximate the La Prosperina Protected Forest scenario, being a dry forest with a low vegetation density compared to other types of forests. The Weissberger model can be used for fire prevention applications with less foliage, making it more accurate in calculations and approximating a realistic environment. Additionally, if we focus on the location of the sensor nodes, the points they mark as references in each scenario must be studied with an implementation in-situ, being able to contrast what is simulated with what is real. Finally, it is expected to be able to couple these algorithms to the wireless sensor network design tool so that the community can use them in their research and test other optimization algorithms that allow us to validate the quantum algorithms in different scenarios.

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**WASHINGTON VELASQUEZ** (Senior Member, IEEE) received the master's degree in telematics services and network engineering and the Ph.D. degree in telematics system engineering from Universidad Politécnica de Madrid, Madrid, Spain. He has authored/coauthored several papers in indexed journals and has led projects related to sensing and networking. He also holds international certifications in UBIQUITI, HUAWEI, and MIKROTIK. He is currently a Professor with the Faculty of Electrical and Computer Engineering, Escuela Superior Politécnica del Litoral, Guayaquil, Ecuador. His research interests include telemetry, remote control, smart cities, and big data.

**FREDDY JIJON-VELIZ** was born in Guayaquil, Ecuador, in 1996. He received the graduate degree in electronics and telecommunications engineering, Guayaquil, in 2021. From June 2020 to October 2020, he was a Research Assistant at the Electricity and Computing Department (FIEC), ESPOL. Since 2019, he has been a Laboratory Assistant, and since 2020, he has been an Assistant Professor with FIEC and an Assistant to the Coordinator of the Telecommunications Career at ESPOL. He has participated in several projects in the electronics area and has been recognized as the Winner and Second Place at the FIEC Electronics Exhibition in consecutive years. He was a Volunteer of the IEEE ESPOL Student Branch, ComSoc.

**MANUEL S. ALVAREZ-ALVARADO** (Member, IEEE) was born in Guayaquil, Ecuador, in 1988. He received the degree in electrical power engineering and the master's degree (Hons.) in physics education from the Escuela Superior Politécnica del Litoral, Guayaquil, in 2011 and 2013, respectively, the M.Sc. degree (Hons.) in power and energy systems from the New Jersey Institute of Technology, Newark, NJ, USA, in 2015, the Ed.D. degree in physics from the National Polytechnic Institute of Mexico, and the Ph.D. degree in power systems from the University of Birmingham, Birmingham, U.K. He is currently a Professor with the Faculty of Electrical and Computer Engineering, Escuela Superior Politécnica del Litoral. His research interests include educational physics, quantum mechanics, renewable energy, and reliability of power systems.