

Comparative analysis of two-ray ground reflection and log-distance propagation models for particle filter based on received signal strength indicator data

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ABSTRACT

This paper investigates based on Received Signal Strength Indicator using particle filtering and three radio propagation models: the hybrid two-ray ground reflection model, the one-slope, and the two-slope log-distance path loss models. To improve robustness against received signal strength indicator fluctuations, all three propagation models are used in a Sequential Importance Resampling particle filter for recursive state estimation. Experimental validation was conducted in an outdoor environment with ESP32-based Wi-Fi devices operating at 2.4 GHz, at antenna heights of 0.5 m, 1.0 m, and 1.5 m, and at distances up to 250 meters. The results show that model performance depends heavily on the distance range, antenna mounting height, and measurement conditions. Although the two-slope log-distance path loss model provided the best fit, none of the evaluated models accurately predicted the experimental data. Applying a particle filter consistently reduced variance and improved overall estimation stability. Among the evaluated combinations, the two-slope model paired with the particle filter yielded the most precise distance estimates.

Keywords: particle filtering, two-ray ground reflection model, log-distance path loss model, radio propagation model, distance estimation.

INTRODUCTION

Nowadays, life without wireless networks seems impossible and unrealistic. As a society, we have grown accustomed to constant access to wireless internet, digital services, and instant information. Mobile devices, such as phones, tablets, and laptops, have become an integral part of our daily lives. In addition to mobile devices, wireless networks are crucial for the operation of many other systems, such as smart homes, monitoring systems, and Internet of Things devices. One specific application of wireless networks is location tracking, which plays a key role in many fields. Its main applications include navigation [1–3] and resource management [4–6]. In the context of location tracking, one of the most important aspects is the accuracy and reliability

of estimating an object's position based on radio signal measurements.

The literature presents numerous localization approaches that employ various radio signal propagation models. Some of the most used models are the theoretical two-ray ground reflection (TRGR) model [7, 8], and the empirical models: OSLDPL [9, 10] and TSLDPL [11–13]. All the mentioned models have their advantages and limitations, and their effectiveness in estimating an object's location depends on the specific characteristics of the propagation environment and the available measurement data.

The two-ray ground reflection model is based on the physical mechanisms of radio wave propagation. It builds on the free-space model developed by Harald T. Friis, a Danish-American radio engineer, by including the presence of the

ground, making it more realistic. In the literature, it is particularly used in open environments, where ground reflection significantly degrades the received signal power. This model is based on the physical properties of the measurement system, such as antenna height, antenna gain, and wavelength. It employs a deterministic approach, which allows for a more accurate representation of actual signal propagation conditions but also requires knowledge of the antenna array geometry and environmental parameters.

Unlike deterministic models, the LDPL model is characterized by a more general approach, grounded primarily in empirical research and statistical analysis. In the literature, this approach is particularly common in heavily urbanized environments [14–16] and in enclosed spaces. Under these conditions, classical geometric analysis becomes insufficient due to the high complexity of the surrounding topography. As a result, deterministic modeling of each component of the electromagnetic field becomes computationally inefficient or even impossible due to the lack of accurate geometric and material data.

A natural extension and improvement of the OSLDPL model is the two-slope log-distance path loss model, which introduces a second path loss exponent (PLE) to better capture signal attenuation across changing topographies. In this approach, the first PLE models shorter distances, while a second PLE takes over once a specific threshold is reached. This critical breakpoint is precisely determined through Fresnel zone analysis, allowing for more realistic simulations in complex urban and industrial environments. Ultimately, the two-slope model provides a more accurate representation of physical phenomena such as line-of-sight (LOS) cutoffs and ground-wave effects, where signal degradation accelerates sharply beyond the breakpoint.

All the models mentioned are used across a wide variety of research and practical scenarios. In the scientific literature, they are commonly used to estimate distances and locate objects, serving as a fundamental tool wherever there is a need to convert physical distance into the signal strength received by a receiver. Beyond theoretical research, these solutions are effective in the smart agriculture concept [13, 17–19] for monitoring devices in farm fields, as well as in robotics [20–22], where they support vehicle navigation in both indoor and outdoor environments. In

the context of the Internet of Things, they enable node localization in wireless networks, which is crucial for resource management and infrastructure optimization. Additionally, these systems are implemented in Vehicular Ad Hoc Networks (VANETs) [23–25] to track vehicle positions and enable intelligent traffic management. In many of these areas, these models are integrated with particle filters, which allow effective accounting for measurement uncertainty and, consequently, a significant improvement in estimation accuracy.

Particle filters [26, 27] are a class of Bayesian sequential estimation methods that approximate the probability distribution of a system's state using a set of random samples called particles. Many variants of particle filters have been described in the literature, such as sequential importance sampling (SIS), auxiliary particle filter (APF) [28, 29], Rao-Blackwellized particle filter (RBPf) [30, 31], or regularized particle filter (RPF) [26, 27, 32]. They differ primarily in their sampling strategies, the methods for updating particle weights, and the resampling methods, resulting in distinct numerical and computational properties. In practice, particle filters are widely used in positioning, navigation, and object tracking systems [33, 34], where they enable effective accounting for measurement uncertainty and improve the accuracy of position estimates. These filters also play a significant role in satellite and inertial navigation, state estimation for flying objects, and digital signal processing—for example, in adaptive spam filtering, network traffic anomaly detection [35, 36], and speech recognition [37, 38].

There are many studies in the literature [39–41] that compare radio signal propagation models and methods for estimating an object's position. However, it is still relatively rare to directly compare a two-ray ground reflection model with a log-distance path loss model, in both versions, within the same measurement setup and using a uniform estimation mechanism. For this reason, it is important to compare those approaches under consistent conditions, accounting for the particle filter's effect on the stability and accuracy of estimation based on received signal strength indicator (RSSI).

This paper focuses on combining these models with the particle filter (PF). This approach aims to determine a more reliable estimate of distance, and ultimately the location of an object, based on received signal strength

measurements. The fundamental research problem is that the relationship between RSSI and actual distance is not strictly deterministic, as it depends on propagation conditions, system geometry, and environmental interference. To address this, the proposed methodology incorporates both analytical models describing signal attenuation and a PF framework to mitigate measurement uncertainty.

The remainder of this paper presents the following structure: Section 2 outlines the methodology, including a detailed description of signal propagation, the particle filter's operating mechanism, and the measurement model. Section 3 evaluates the particle filter's effectiveness and compares the performance of three propagation models using experimental results. Finally, Section 4 discusses these results, presenting conclusions and directions for future research.

THEORETICAL APPROACH

The research methodology was organized into a sequence of successive stages, from the description of signal propagation to sequential filter estimation. First, models were defined that relate received power to the distance between the transmitter and receiver. These relationships were then used in the observation model in a particle filter, which updates the estimate based on successive RSSI samples. This setup allows for the separation of two levels of analysis: the deterministic description of signal fading and the probabilistic account of measurement uncertainty.

This section discusses the propagation models used in the study: the first is a hybrid approach that uses the free-space path loss (FSPL) model for short distances and a simplified two-ray ground reflection model for longer distances. This design results from the limitations of the simplified TRGR model at short distances. It allows the description to remain consistent with the antenna array geometry while achieving more stable performance across the entire analyzed range. The second approach considered is the one-slope log-distance path loss model, in which signal attenuation is described by a Path Loss Exponent determined based on measurement data. The third solution analyzed is the Two-Slope Log-Distance Path Loss model, which extends the OSLDPL approach by introducing a breakpoint that divides the propagation path into two regions with

different Path Loss Exponents. The combination of these three models provides a comprehensive basis for further comparison of the strictly physical, empirical, and hybrid approaches, which combine the simplicity of statistical models with the spatial characteristics of the radio channel.

Based on the propagation layer defined in this manner, an estimation model utilizing the sequential importance resampling (SIR) particle filter was developed. In this approach, the system state represents the searched distance, while the measurement model assesses the consistency between the predicted and observed RSSI values. Subsequent weighting and resampling steps reduce the impact of short-term signal fluctuations and approximate the *a posteriori* distribution of the estimated quantity. The following subsections present the mathematical formulations of the TRGR and LDPL models, respectively, along with the method for integrating them into the filtering procedure.

Two-ray ground reflection model

The physical basis of the hybrid approach under analysis is the two-ray ground reflection model, which describes signal propagation as a superposition of the direct component and the wave reflected from the ground. This model relates the received power to the geometry of the measurement system, to the distance between devices, antenna mounting heights, wavelength, and therefore serves as a natural starting point for further describing the dependence of RSSI on distance. To express this mathematically, the lengths of both propagation paths are first determined: the direct path (1) and the path reflected from the ground (2).

$$d_1 = \sqrt{d^2 + (H_T - H_R)^2} \quad (1)$$

$$d_2 = \sqrt{d^2 + (H_T + H_R)^2} \quad (2)$$

where: d is the distance between the transmitter and the receiver, H_T is the height at which the transmitter antenna is mounted, and H_R is the height at which the receiver antenna is mounted.

In the TRGR model, the received power $P_{RT}(d)$ accounts for both direct and reflected signal paths, along with key system parameters. It is expressed as:

$$P_{RT}(d) = P_T G_T G_R \left(\frac{\lambda}{4\pi} \right)^2 \left| \frac{e^{-jkd_1}}{d_1} - \frac{e^{-jkd_2}}{d_2} \right|^2 \quad (3)$$

where: P_T is transmitter power, G_T is transmitter antenna gain, G_R is receiving antenna gain, λ is wavelength, k is wave number calculated from $k = 2\pi/\lambda$, and d_1 and d_2 are the lengths of the direct and reflected paths, respectively.

Despite its accuracy, this model unfortunately cannot be used to estimate distance due to its mathematical properties. For distances shorter than the critical distance (4) [42], the model exhibits significant fluctuations in received power, making it difficult to assign a specific RSSI value to a given distance unambiguously. For this reason, a simplified version of this model is often used in practice, as it is more stable and easier to apply in real-world localization scenarios.

The critical distance (d_c) is the limiting distance between the transmitter and the receiver, which depends on the height of both antennas and the wavelength.

$$d_c = \frac{4\pi H_T H_R}{\lambda} \quad (4)$$

Below this value, interference between the direct and reflected waves becomes dominant, leading to significant fluctuations in the received power.

For distances greater than the critical distance, signal attenuation increases uniformly at

a rate of d^{-4} , which allows the model to be simplified to a logarithmic form (5). This simplified variant is commonly known in the literature as the simplified two-ray ground reflection model. It reduces computational complexity while preserving key features of signal propagation, such as the effects of antenna height and distance. As a result, signal propagation becomes predictable and easier to model.

$$P_{RS}(d) = P_T + G_T + G_R + 20 \log_{10} \left(\frac{H_T H_R}{d^2} \right) \quad (5)$$

For distances shorter than the critical distance, the two-ray ground reflection model suffers from fluctuations that prevent reliable RSSI-to-distance assignment. In the same range, the simplified model also fails to represent the full model accurately. These issues are shown in Figure 1. Therefore, in many studies [42–44], researchers have opted to use the free-space path loss model (6) at shorter distances and the simplified TRGR model at longer distances.

$$P_{RF}(d) = P_T + G_T + G_R - 20 \log_{10} \left(\frac{4\pi d}{\lambda} \right) \quad (6)$$

This results in a hybrid model (7) that combines the advantages of both models, thereby ensuring greater accuracy across a wide range of localization scenarios. This model enables more precise estimation of received power, as shown in Figure 2, which is crucial for effective localization, especially in environments with varied topography and different signal propagation conditions.

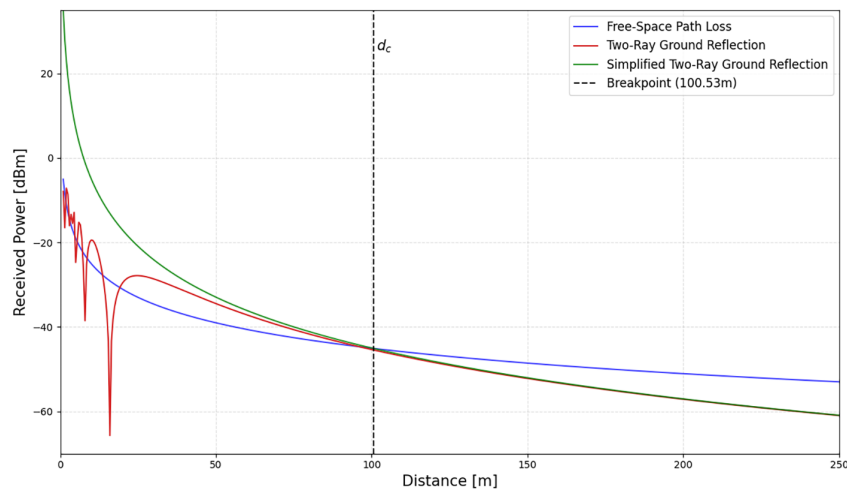


Figure 1. Dependence of received power on the distance between the transmitter and receiver for the following models: The two-ray ground reflection, simplified two-ray ground reflection, and free-space path loss

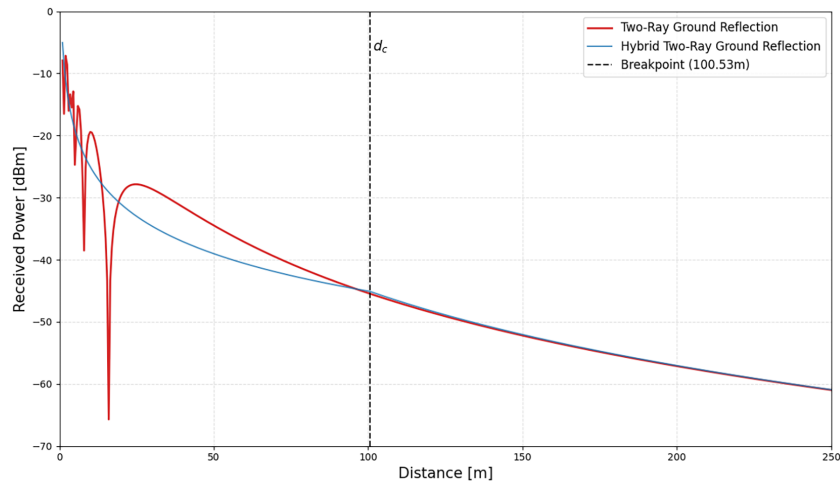


Figure 2. Dependence of received power on the distance between the transmitter and receiver for the following models: Hybrid and two-ray ground reflection

$$P_{RH}(d) = \begin{cases} P_{RF}(d), & d \leq d_c \\ P_{RS}(d), & d > d_c \end{cases} \quad (7)$$

Log-distance path loss model

The second approach analyzed in this paper is the log-distance path loss model, which provides an empirical alternative to theoretical methods based strictly on propagation geometry. Traditionally, path loss models are divided into two main categories: One-slope and two-slope models [12, 45, 46].

In the one-slope model, the relationship between received power and distance is presented in logarithmic form. The key parameter remains the path loss exponent (n), which allows the signal fading characteristics to be adapted to actual measurement conditions. For this reason, this model serves as a natural reference point for the hybrid approach and is subsequently expressed as Equation 8, which relates the RSSI value to the distance from the transmitter.

$$P_{RL}(d) = P_R(d_0) - 10n \log_{10} \left(\frac{d}{d_0} \right), \quad (8)$$

where: d_0 is the reference distance, and. $P_R(d_0)$ is the received power at the reference distance.

This equation describes signal loss using two quantities with direct practical interpretations: the reference power $P_R(d_0)$ and path loss exponent (n). The former provides a reference point for estimation, while the latter determines the rate at which

power decreases with increasing distance. This allows the model to be easily calibrated for a specific measurement environment. The typical ranges of path loss exponent values are listed in Table 1 based on data reported in the literature [9, 47].

The two-slope model, on the other hand, provides a more realistic representation of signal attenuation by accounting for two distinct propagation regions. The first region assumes wave propagation in free space. The second region is characterized by additional environmental factors, such as obstacles, reflections, and diffraction, that further attenuate the signal.

In propagation modeling, breakpoint defines the specific distance at which signal propagation characteristic change due to physical or environmental factors. The Perera breakpoint,

$$d_p = \frac{4H_T H_R}{\lambda} \quad (9)$$

This is an empirical modification of the classical Fresnel breakpoint that was proposed to

Table 1. The typical values of the PLE for various propagation environments

Environment	Path loss exponent
Free space	2
Urban areas	2.7–3.5
Shadowed urban cellular radio	3–5
In building line-of-sight	1.6–1.8
Obstructed in buildings	4–6
Obstructed in factories	2–3

better represent radio propagation in urban and suburban environments [48].

The two-slope log-distance path loss (see Equation 10) model typically provides a much better fit to experimental data than its one-slope counterpart, as it adapts to changes in the propagation environment with distance. Consequently, this paper employs a two-slope approach based on the foundational one-slope log-distance path loss model to more accurately capture real-world signal attenuation.

$$P_{RLDS}(d) = \begin{cases} P_R(d_0) - 10n_1 \log_{10}\left(\frac{d}{d_0}\right), & d \leq d_p \\ P_R(d_0) - 10n_1 \log_{10}\left(\frac{d_f}{d_0}\right) - 10n_2 \log_{10}\left(\frac{d}{d_f}\right), & d > d_p \end{cases} \quad (10)$$

Comparing three models, the Hybrid TRGR model, the OSLDPL model, and the TSLDPL model, is important because each has its own advantages and limitations. The two-ray ground reflection model is more detailed and accounts for specific propagation mechanisms, but it may be less practical in complex environments. In contrast, the one-slope log-distance path loss model is simpler and more versatile, but it may not capture all the nuances of signal propagation under various conditions. Finally, the two-slope log-distance path loss model provides a more flexible approach by allowing different propagation characteristics across distance ranges, thereby enabling better fitting of experimental data. By

comparing these models, researchers can determine which is most suitable for a given application and environment, balancing accuracy and computational efficiency.

Particle filter

From a location perspective, the particle filter acts as an estimation layer that combines information obtained from the propagation model with actual signal measurements. Propagation models define the relationship between distance and received power. However, a single RSSI measurement is typically highly variable and should not be interpreted deterministically. The particle filter accounts for this uncertainty by combining successive observations and gradually narrowing down the range of possible object locations. It is an extremely effective tool for state estimation in nonlinear and non-Gaussian systems. It allows for a more stable estimate than directly converting individual RSSI samples into distance.

This paper uses the sequential importance resampling particle filter presented in Algorithm 1. It is one of the most popular and simplest variants of particle filters [26, 49–51]. It extends the sequential importance sampling (SIS) approach with a resampling step, thereby eliminating particle weight degeneration and ensuring a stable approximation of the posterior distribution in subsequent steps.

input : z - One dimensional measured data array
 N_s -number of experimental points,
 N -number of added particles,

output: x - calculated values array

for $k = 1$ **to** N **do**
 | Prepare N random particles and assign base state
end
for $k = 1$ **to** N_s **do**
 for $i = 1$ **to** N **do**
 | Calcualte N samples from (11) and corresponding weights from (12)
 end
 Calculate total weight: $w_s = \sum_{i=1}^N w_k^i$
 for $i = 1$ **to** N **do**
 | Normalize weights: $w_k^i = w_k^i / w_s$
 end
 Particle resampling
 Assign de-noised value x_k using weighted mean (14)
end

Algorithm 1. Sequential importance resampling particle filter

The Sequential Importance Resampling particle filter consists of three stages: propagation, weighting, and resampling, and operates by recursively updating the *a posteriori* distribution of the system's state. In practice, this distribution is replaced by a finite set of N weighted particles, in accordance with the discrete representation described by the equation:

$$p(x_k | z_{1-k}) \approx \sum_{i=1}^N w_k^i \delta(x_k - x_k^i) \quad (11)$$

where: x_k is the estimated distance at time k , z_k is the received signal strength measurement at time k , w_k^i where the weight of the i -th particle at time k .

In each step of the algorithm, the particles are first propagated according to the motion model, and then their weights are updated based on their agreement with the new observation. The general form of the weight update follows the weighted sampling principle and is given by the equation:

$$w_k^i \propto w_{k-1}^i \frac{p(z_k | x_k^i) p(x_k^i | x_{k-1}^i)}{q(x_k^i | x_{k-1}^i, z_k)} \quad (12)$$

where: $p(z_k | x_k^i)$ is the measurement likelihood defined by the observation model, which specifies the probability density of obtaining measurement; $p(x_k^i | x_{k-1}^i)$ is the state transition probability density governed by the system motion model, describing the state evolution between successive time steps; and $q(x_k^i | x_{k-1}^i, z_k)$ is the proposal distribution, which defines the probability density of sampling state x_k^i based on the previous state x_{k-1}^i and current observation z_k .

In the first step, N particles are generated to represent the possible initial states of the system. To account for uncertainty, the particle filter incorporates process noise (s). Our particle filter uses the highest value of the standard deviation recorded during our measurements. The initial state distribution is commonly generated using a Gaussian distribution centered around the state predicted by the propagation model, given by:

$$p(z_k | x_k^i) = \frac{1}{\sigma \sqrt{2\pi}} \exp\left(-\frac{(z_k - P_R(x_k^i))^2}{2\sigma^2}\right) \quad (13)$$

where: z_k is the received signal strength measurement at time k , x_k^i is the state hypothesis (estimated distance) of the i -th particle at time k , $P_R(x_k^i)$ is the received power at distance x_k^i described by the propagation model, and s is the height's standard deviation of the measurement data.

This paper adopts two approaches, depending on the wave propagation model used. In the hybrid two-ray ground reflection model, a theoretical value is calculated, and noise is added from a normal distribution. In the case of both log-distance path loss models, particles are generated based on a normal distribution centered around the path-loss exponent. The value of n is selected from 0 to 5.

Based on previous research [10, 27, 52], a value $N=1000$ was adopted as a compromise between estimation accuracy and computational complexity. This value ensures sufficient representation of the posterior distribution while keeping computation time at an acceptable level for real-time applications.

In the next step, each particle is assigned a weight that reflects the degree of agreement with the observation. The weights are updated using a measurement model that estimates the probability of obtaining a specific observation under a given state hypothesis.

The final step involves resampling, which generates a new set of particles based on their weights. For this purpose, a commonly used systematic resampling method [53–55] was selected, which ensures a uniform distribution of particles. Resampling avoids weight degeneracy caused by favoring stronger particles, allowing us to focus on the most likely state hypotheses. To obtain the new estimated values, normalize the particle weights $w_k^i = w_k^i / w_s$, and then calculate the result using the equation:

$$x_k = \sum_{j=1}^N x_k^j w_k^j \quad (14)$$

where: x_k – the estimated distance at time k , x_k^j – the value of the j -th particle at time k , and w_k^j – the weight of the j -th particle at time k .

EXPERIMENT SETUP

The experiment was carried out in a controlled environment that allowed for accurate measurements of the received signal strength as a function

of distance. All measurements were taken outdoors, at an environmental temperature of approximately 20 °C and a relative humidity of 50–55%. Two Wi-Fi devices based on ESP32 microcontrollers were used, operating in the 2.4 GHz band (802.11 b/g/n), equipped with a dual-core processor clocked at up to 160 MHz, and with interfaces enabling stable recording of measurement data to flash memory. Each device was paired with an external antenna with a gain of 3 dBm, ensuring comparable transmission and reception conditions and minimizing the impact of hardware differences on the results. Additionally, fixed transmission parameters (same channel bandwidth, transmit power, and network configuration) were used to isolate the effects of distance and system geometry from the effects of the radio configuration as much as possible.

One of the devices, which continuously broadcast a Wi-Fi network, was set to Access Point mode and operated as a stationary reference transmitter. The second device served as a measurement receiver and, at regular intervals, initiated a connection to the broadcast network, reading the RSSI value once the connection was established. Experiment visualization is presented in Figure 3. After a single reading was taken, the connection was terminated, and the procedure was repeated, allowing a series of independent samples to be obtained at a given distance. This operating mode minimized the impact of short-term fluctuations and enabled subsequent averaging and statistical analysis of the results. Data from each cycle, along with a timestamp and information about the measurement configuration, was saved to a file stored in the device's flash memory. After completing a series of measurements, the data were downloaded to a computer and analyzed further.

The experiment was repeated at various distances between the transmitter and receiver, starting at a few meters and gradually increasing to 250 meters. Additionally, to account for ground reflection, the experiment was conducted with different antenna mounting heights (0.5 m, 1.0 m, and 1.5 m), allowing an assessment of its impact on distance estimation accuracy. In this study, the mounting heights of the transmitter and receiver antennas were always identical, i.e. $H_A = H_T = H_R$, where H_A denotes the general antenna height. This made it possible to compare the results with all three propagation models, two-ray ground reflection, one-slope log-distance path loss, and two-slope log-distance path loss, and to evaluate the effectiveness of the particle filter in distance estimation based on RSSI measurements.

RESULTS

A series of measurements was conducted outdoors to evaluate signal propagation between two Wi-Fi network nodes over distances ranging from 1 to 250 m. To perform a comparative analysis, theoretical calculations were carried out in parallel using both log-distance path loss models, and the hybrid two-ray ground reflection model, accounting for varying antenna mounting heights.

The results are presented in Figure 4. The presented data exhibit a distinct logarithmic trend, a direct consequence of the geometric attenuation of radio waves with distance. However, the experimental curves show local fluctuations in signal strength resulting from fading and multipath interference [56, 57].

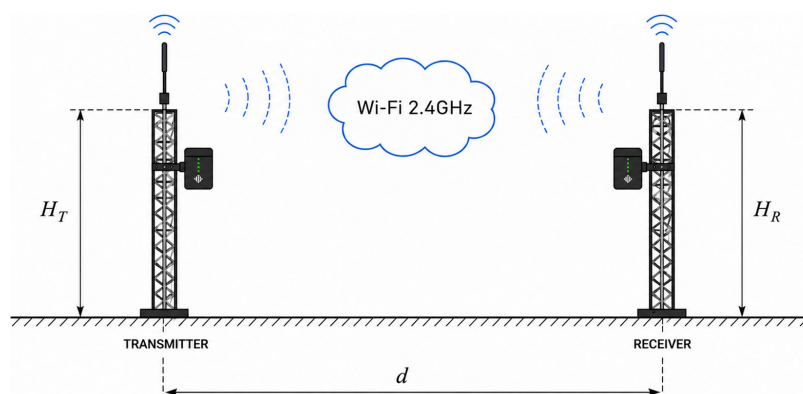


Figure 3. Experimental setup for measuring RSSI values at various distances and antenna mounting heights
The transmitter is set to Access Point mode, while the receiver periodically connects to the network to record RSSI values

The measurement errors observed are directly related to the technical specifications of the testing equipment and to dynamic changes in environmental conditions. To quantify this uncertainty, the average standard deviation of the collected experimental data was calculated, with the results summarized in Table 2.

In the first approach, the One-Slope Log-Distance Path Loss model was used. The analysis of the collected data indicates that increasing the antenna mounting height results in a monotonic decrease in signal attenuation. This dependency is directly reflected in the calculated PLE values. The values of the path loss exponent were approximated using the Scilab computational package for the measurement points. For an antenna height of 0.5 m, this parameter reaches $n = 2.644$, which aligns closely with literature data typical of

Table 2. The mean standard deviations of RSSI measured data for different antenna mounting heights

Antenna mounting height [m]	Mean standard deviation [dBm]
0.5	1.378
1.0	1.361
1.5	1.670

urbanized propagation environments. Conversely, for the remaining higher antenna placements, the estimated PLE values closely match reference values characteristic of open-space environments (see Table 1). The analysis reveals that while the One-Slope Log-Distance Path Loss model provides an acceptable approximation of the general trend of signal power decrease, it does not fully capture the complexity of the actual measurement data.

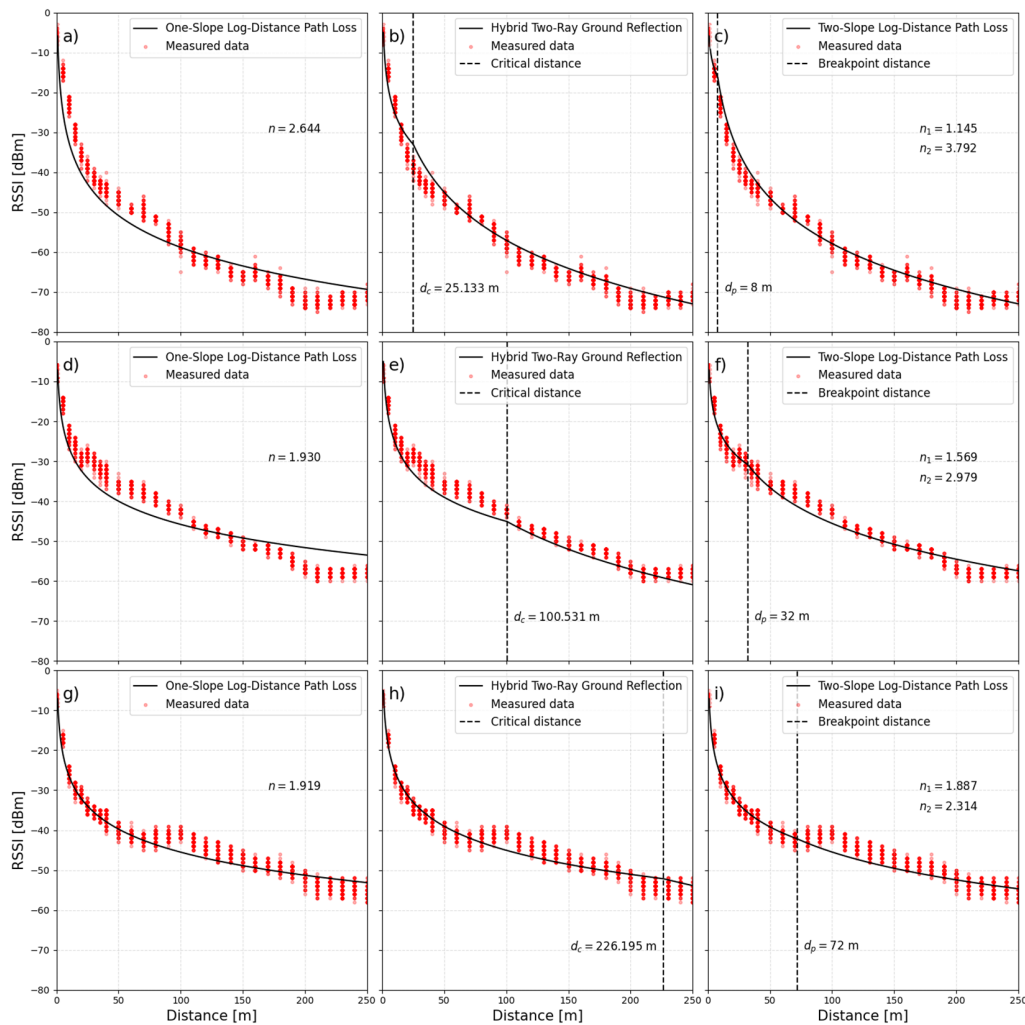


Figure 4. The RSSI measurement data and calculated the hybrid two-ray ground reflection model, one-slope log-distance path loss model and two-slope log-distance path loss model for distances ranged from 1 to 250 meters and different antenna mounting heights, equals to 0.5 m (parts a, b, c) and 1 m (parts d, e, f) and 1.5 m (parts g, h, i), respectively

Figure 4 (parts b, e, h) shows the effects of using the hybrid two-ray ground reflection model. Despite its theoretical approach, this model appears to be the better solution. This model shows significantly higher effectiveness in reproducing experimental results.

The next model under consideration is the two-slope log-distance path loss model. This appears to be a promising approach due to the characteristic shape of the curves. Approximating it with two logarithmic curves should yield good results. Table 3 presents the estimated PLE values for various antenna mounting heights and propagation models derived from the experimental data. These values demonstrate that signal propagation characteristics vary significantly with antenna installation height.

Utilizing the Two-Slope model with the determined exponents provides a much more accurate fit to the measured data (see Figure 4, parts c, f, i). This indicates that the Two-Slope approach is better suited for capturing the complex behavior of real-world signal propagation, where factors such as multipath effects and environmental obstacles significantly influence the received signal strength.

In practice, it is difficult to determine whether the approximated results better or worse reflect the experimental data. What is needed is a measure that shows how well the models used represent the experimental data. Therefore, to precisely assess the quality of obtained results, the peak signal-to-noise ratio (PSNR) [58, 59] was introduced as an additional metric.

In general, this metric is used in image processing to evaluate the quality of image

compression and reconstruction. The formula originally describes it:

$$PSNR = 10 \cdot \log_{10} \left(\frac{D^2}{MSE} \right) \quad (15)$$

where: D^2 is the maximum possible signal value, and MSE is the mean squared error. For the experimental data under study, this metric was defined as follows:

$$PSNR = 10 \cdot \log_{10} \left(\frac{(P_{\max} - P_{\min})^2}{MSE} \right) \quad (16)$$

where: $P_{\max}$ and $P_{\min}$ are, respectively, the maximum and minimum data values in each dataset. In our case, the values of MSE were calculated from the following formulae:

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (17)$$

where: n is the number of data points, y_i is the theoretically calculated value from the considered models and $\hat{y}_i$ is the experimental value.

The metric constructed in this way enables the assessment of the fit of the models used to the experimental data. High PSNR values correspond to a lower error threshold, indicating a better fit of curves calculated from the model data to the experimental data.

The results of the mean PSNR calculations for various wave propagation models and antenna mounting heights, for experimental data, are presented in Table 4.

Table 3. The PLE values for different antenna mounting heights and used propagation models

Antenna mounting height [m]	Path loss exponent one-slope N	Path loss exponent two-slope	
		n_1	n_2
0.5	2.644	1.145	3.792
1.0	1.930	1.569	2.979
1.5	1.929	1.887	2.314

Table 4. The PSNR data for experimental RSSI values for different antenna mounting heights and propagation models

Antenna mounting height [m]	Hybrid TRGR [dB]	OSLDPL [dB]	TSLDPL [dB]
0.5	27.190	24.006	28.612
1.0	24.988	22.509	28.410
1.5	27.102	27.251	29.402

The results presented in Table 4 clearly indicate that the two-slope log-distance path loss model better reproduces the experimental data compared to the other models. The highest PSNR values indicate the best possible fit of the TSLDPL model curves to the experimental data. Unfortunately, the data on which the calculations were based are subject to measurement error. The standard deviation values presented in Table 2 are quite large. This error translates directly into the calculated PLE values. Due to the stochastic nature of signal fluctuations and the nonlinearity of propagation mechanisms, conventional deterministic methods prove insufficient. Under such conditions, particle filtering algorithms demonstrate high effectiveness. Figure 5 compares actual experimental data with particle filter estimates for two representative distances: 10 m and 100 m for antenna mounting heights equal to 0.5 m.

Table 5 presents the values of the mean standard deviation obtained for all the propagation models and antenna positions used.

The presented results explicitly confirm the usefulness of particle filters for estimating RSSI across all models under consideration. Regardless of the wave propagation model applied, the filter consistently matches experimental data and effectively minimizes the mean standard deviation. At the same time, maintaining high estimation accuracy relative to the baseline propagation models. For comparison, PSNR values were also calculated based on data obtained from the Bayesian filter. The results are presented in Table 6.

The data presented in Table 5 and 6 shows that the use of a particle filter increases the PSNR values for all propagation models, as reflected by the mean standard deviation values shown in Table 5. Furthermore, the highest PSNR values

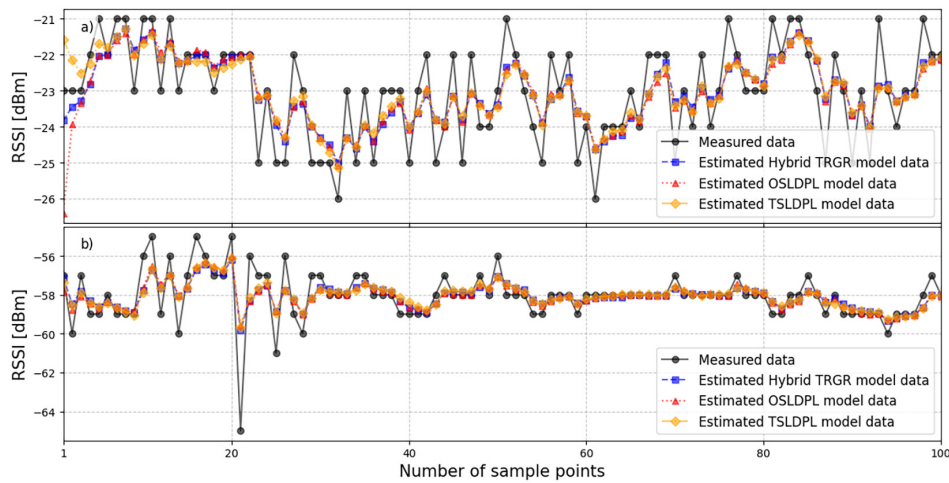


Figure 5. The measured RSSI data and particle filter estimation results for 1000 particles at 10 m (part a) and 100 m (part b), based on 100 experimental data points. The antenna mounting height is equal to 0.5 m

Table 5. The mean standard deviations of RSSI data after particle filter estimation at different antenna placements

Antenna mounting height [m]	Mean standard deviation of RSSI data		
	OSLDPL [dBm]	Hybrid TRGR [dBm]	TSLDPL [dBm]
0.5	0.651	0.637	0.628
1.0	0.554	0.534	0.520
1.5	0.785	0.783	0.782

Table 6. The PSNR data for estimated RSSI values for different antenna mounting heights and propagation models

Antenna mounting height [m]	Hybrid TRGR [dB]	OSLDPL [dB]	TSLDPL [dB]
0.5	28.260	24.656	30.099
1.0	25.583	24.656	30.036
1.5	28.333	28.842	30.128

are observed for the TSLDPL model for both experimental and estimated data.

The main goal of this study was to investigate the effects of using the particle filtering method and of the choice of propagation models on the estimation of distance from measured RSSI values. Moreover, the obtained path loss exponents and their corresponding PSNR values do not directly provide information about the distance estimation error. So, we calculate the absolute distance estimation error (ADEE) using the following expression:

$$d_{err}(i) = |d_M(P_R(i)) - d_E(P_R(i))| \quad (18)$$

where: $d_M(P_R(i))$ corresponds to the distances calculated from the models (hybrid TRGR, OSLDPL, and TSLDPL), and $d_E(P_R(i))$ corresponds to the distances obtained from experimental data for the same RSSI values ($P_R(i)$).

The distance estimation errors were calculated for distances equal to 15, 50, 100, 150, and 200 meters. When analyzing the obtained results, the logarithmic relationship between the RSSI signal and distance should be considered. A small error in RSSI measurement at short distances translates into a relatively small error in the measured distance. Unfortunately, for longer measured

distances, this error is much larger. Table 7 summarizes calculated distance estimation error values for different models and antenna mounting heights for experimental and estimated data.

The absolute distance estimation error values presented in the table are characterized by a considerable discrepancy. The absolute distance measurement error varies from a fraction of a meter to hundreds of meters. Comparing the $d_{err}(i)$ values for the models used, one can observe the advantage of the TSLDPL over other models. However, it should be noted that it is not a perfect solution. The poorest results were obtained for the theoretical TWRG model, which had the highest distance estimation errors. A decrease in this error was observed with increasing antenna mounting height. This phenomenon results from a reduction in the contribution of ground reflections and multipath, which in turn improves line-of-sight (LoS) transmission conditions and reduces systematic measurement error. This relationship is also confirmed by publications [60, 61], which showed that higher antenna placement weakens the influence of reflected signals, increasing the precision of distance estimation. Furthermore, the use of a particle filter resulted in a slight reduction in the $d_{err}(i)$ values for most cases. As in the case of raw data (without using a filter), the TSLDPL model showed the smallest error.

Table 7. The absolute distances estimation error for measured and estimated RSSI values for different antenna mounting heights and different propagation models

Antenna height [m]	Real distance [m]	Hybrid TRGR		OSLDPL		TSLDPL	
		ADEE for experimental data [m]	ADEE for particle filter data [m]	ADEE for experimental data [m]	ADEE for particle filter data [m]	ADEE for experimental data [m]	ADEE for particle filter data [m]
0.5	15	2.7	5.4	6.9	5.9	3.4	4.8
	50	59.5	68.8	15.6	10.6	0.2	5.1
	100	112.0	111.6	6.4	6.0	0.9	0.7
	150	188.5	180.2	40.0	34.6	15.2	12.0
	200	282.5	271.4	125.0	110.3	40.2	35.0
1.0	15	3.6	3.5	5.4	5.5	1.3	1.3
	50	13.8	12.9	18.1	17.2	1.4	0.6
	100	25.7	20.2	32.8	28.7	21.3	17.9
	150	11.5	10.5	28.4	28.1	1.7	0.7
	200	1.0	8.2	185.9	217.8	44.5	59.1
1.5	15	1.8	3.6	0.3	1.5	0.4	2.2
	50	5.0	1.8	0.7	5.2	4.2	2.2
	100	38.5	41.5	43.0	45.8	39.0	42.2
	150	37.9	26.5	30.6	4.3	33.9	12.2
	200	52.4	58.2	11.9	4.2	13.2	26.9

Observing the data presented in Figure 4 (parts c, f, i), it is easy to notice a slight mismatch of the TSLDPL model, especially for the highest mounted antenna. For approximately 100 m, a slight signal amplification is observed. In [48], the authors proposed a modification of the Perera breakpoint. This modification, known as the true breakpoint (d_p), allows for better optimization of the TSLDPL model to

experimental data. It is defined as a scaled version of the Perera distance: $d_T = \alpha d_p$, where α is a scaling factor that can be adjusted based on actual measurement data. Calculations were performed by varying the correction factor from 1.0 to 1.4. In each case, ADEE values were calculated both before and after filtering. The lowest ADEE values for the model under consideration were obtained with a scaling

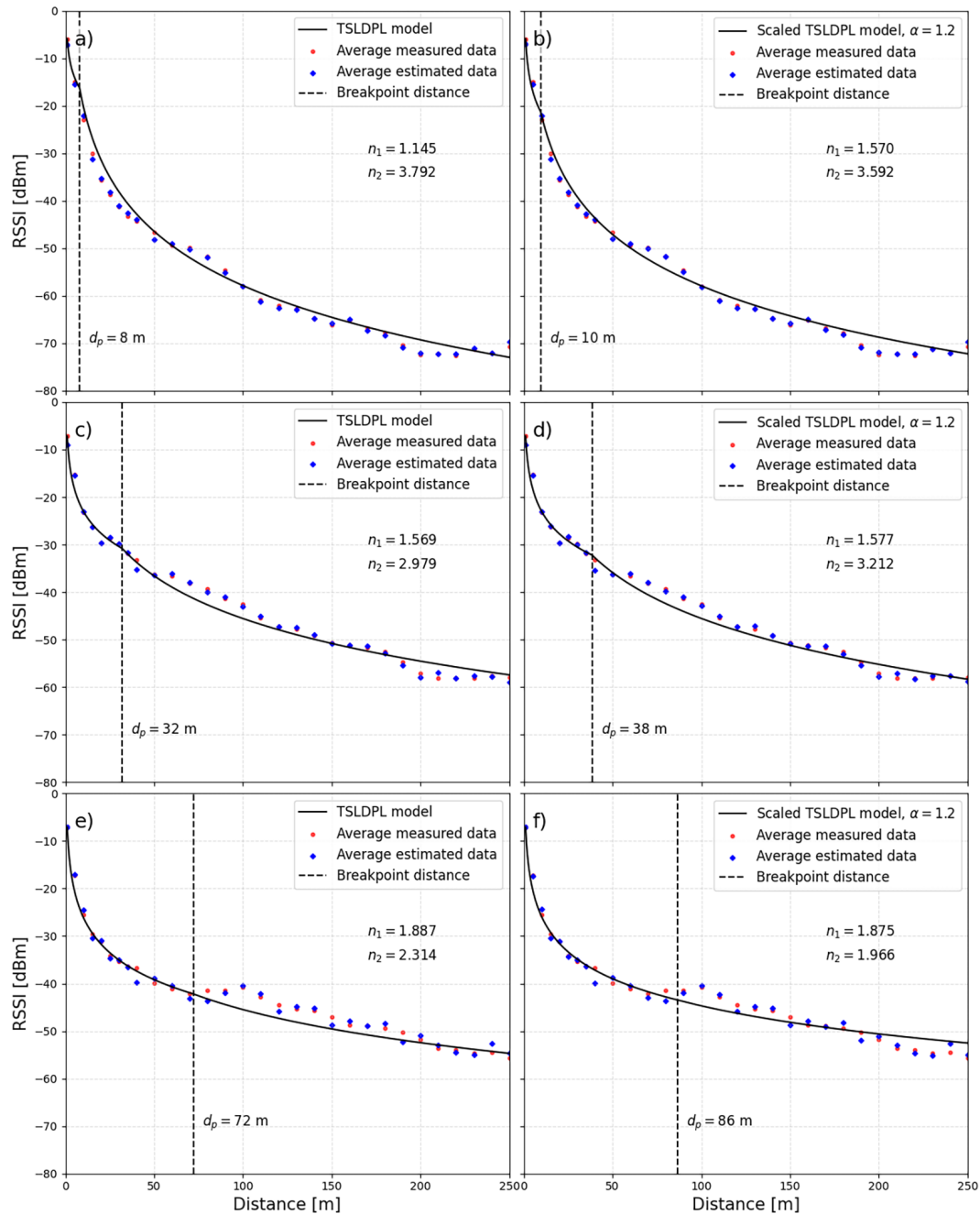


Figure 6. The experimental RSSI data and estimated data against the two-slope log-distance path loss model, and scaled two-slope log-distance path loss model ($\alpha=1.2$) for distances ranged from 1 to 250 meters and different antenna mounting heights, equals to 0.5 m (parts a, b) and 1 m (parts c, d) and 1.5 m (parts e, f), respectively

Table 8. The absolute distances estimation error for measured and estimated RSSI values for different antenna mounting heights and scaled TSLDPL propagation model

Antenna height [m]	Real distance [m]	TSLDPL ($\alpha=1.2$)	
		ADEE for experimental data [m]	ADEE for particle filter data [m]
0.5	15	1.7	1.1
	50	1.8	1.7
	100	0.7	1.0
	150	19.5	15.3
	200	51.6	43.3
1.0	15	1.0	0.7
	50	1.2	1.3
	100	19.8	17.2
	150	5.7	4.8
	200	29.4	41.1
1.5	15	0.7	0.6
	50	5.6	1.1
	100	37.4	39.9
	150	19.3	9.1
	200	28.9	12.4

factor of 1.2. The calculation results presented in Table 8 indicate that the empirical selection of the scaling factor significantly reduced the error. The obtained logarithmic curves fit the experimental data much more precisely.

Unfortunately, the obtained results are not entirely satisfactory, as introducing a scaling factor reduced the error in some cases but increased it in others. Applying a particle filter eliminates this error, demonstrating the filter's effectiveness. Figure 6 compares the two TSLDPL models used on experimental data. Additionally, the figure shows the average values of the estimated and experimental data. The particle filter significantly reduces the statistical error. But the RSSI data exhibit a different type of variation that the filter cannot compensate for. The data do not exhibit a typical logarithmic pattern, and therefore neither model is able to capture this variation. In the case of wave propagation, the received signal may be weakened or strengthened by physical processes such as diffraction, interference, scattering or shadowing. Even in measurements performed in open spaces [62].

CONCLUSIONS

Data obtained from experiments are always affected by measurement error, resulting from the technical limitations of the measuring equipment and variable environmental conditions. Particle Filters are a commonly used tool for improving data quality. By applying this solution in our case, we obtained data with significantly reduced interference and signal fluctuations. The most important results from this study include the following:

- The particle filter reduces the variance of the data, leading to more accurate predictions of the path loss exponent.
- The scaled two-slope log-distance path loss model provides the best fit to the experimental data, suggesting that it is more effective at predicting signal propagation in the studied environment.
- The use of the particle filter in combination with the two-slope log-distance path loss model yields the most precise distance estimates, which is important for radio-based positioning and navigation systems.
- The height at which the antennas are mounted has a significant impact on signal quality and distance-estimation accuracy, with higher antenna placement resulting in lower signal loss.

In summary, other models more precisely tailored to the conditions under which the measurements were conducted should be considered. This could potentially allow for a more precise consideration of the influence of terrain surface structure and local environmental characteristics. This would provide an answer to the question of what happened during the measurement and why the models used did not produce accurate results, despite their correct application.

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