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Optimizing Wi-Fi-based Positioning Systems using Intelligent Weight Distribution and Fuzzy Logic Techniques

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ABSTRACT

The application of indoor localization systems has exponentially risen in recent years as its use cuts across several localization-based services. There exist several variants of indoor position systems in literature with the recent variants of the indoor positioning systems being improved with by using one or Multi-Criteria Decision Making (MCDM) techniques to improve the criteria of the localization system. However, these metrics suffer from computational costs and decision bias, which can affect its application in other indoor localization environments. This research adopts an approach that splices two MCDM techniques to develop the infrastructure for a centimetre-level-based localization model. The first of the MCDM, which is Simple Additive Weighting (SAW) considers a selected number of criteria to develop the initial infrastructure for localization. This is further improved by the second MCDM, which is, Fuzzy Analytic Hierarchy Process (FAHP) to modify the weights assigned to the aforementioned criteria to mitigate deviations and achieve better indoor positioning results. Simulation results showed that the model achieved an average localization error of 25cm with a precision of 30cm, which shows the models applicability in indoor settings. Alongside the mean signal strength and RSSI variance, the proposed model showed a considerable level of adaptability for indoor positioning applications.

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INTRODUCTION

Multiple positioning systems have been proposed as a result of the exponential growth of wireless technology, multisensory systems, and autonomous systems. The variations in these positioning systems is based on the technology adopted, the form of sensory information, level of accuracy, the protocol adopted for communication, and the algorithm developed or adopted. These variations in approaches that are introduced to the positioning system to improve it consequently imposes a considerable amount of uncertainty and vagueness that introduces challenges to the system (Alakhras *et al.*, 2020). To address these challenges, there are several approaches in literature (Aydin & Seker, 2021; Budak *et al.*, 2020; Budak & Ustundag, 2015; Jurdi *et al.*, 2024; Rathnayake *et al.*, 2023; Wang *et al.*, 2019;Ayo-Bello *etal.*,2022) that have been tailored to the technologies these localization technologies are built atop (Giwa, Igbax, *et al.*, 2024; Kargar-Barzi *et al.*, 2024). Though this work focuses specifically on Wi-Fi-based localization technologies due the availability of the infrastructure Alabi *et al.,* (2023).

To account for this hurdle of vagueness and uncertainties, fuzzy-logic-based localization systems are explored as a pragmatic solution to address the aforementioned hurdles (Budak *et al.*, 2020; Cil *et al.*, 2021; Cil *et al.*, 2022). The framework for fuzzy sets and fuzzy inference systems take into account the granularity and flexibility of human knowledge, which are characteristics of complex system behaviours that do not explicitly require exact mathematical models or situations where a comprehensive list of factors that must be understood is unknown (Alakhras *et al.,* 2020). On this premise, this paper

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presents a technique that combines two Multi-Criteria Decision Making (MCDM) schemes, namely: Simple Additive Weighting (SAW) and Fuzzy Analytic Hierarchy Process (FAHP). For this work, SAW considers a selected number of criteria to develop the initial infrastructure for localization. Then it is further improved by the second FAHP to modify the weights assigned to the aforementioned criteria to mitigate deviations and achieve better indoor positioning results.

The remaining sections discusses the following. Section 2 presents a review of similar literature. The methodology of the proposed method is shown in section 3. Section 4 presents the performance metrics considered in this work. The results and discussion are presented in sections 5 and 6, respectively. Section 7 concludes the work, while the definition of terms is discussed in section 8.

LITERATURE REVIEW

The work of (Budak *et al.*, 2020) proposed a RTLS system to identify and select the optimal warehouse for humanitarian relief logistics. The authors spliced an approach that considered the benefits and risk factors with IVIF MCDM approach to address the fuzziness in decision-making. Additionally, a combination of IVIF-DEMATEL was adopted to separate the inner and outer dependencies of the criteria. Furthermore, a combination of IVIF-ANP was used to obtain the weights of the sub-criteria. Finally, the authors used IVIF-TOPSIS to identify and select the best RTLS to be adopted for human logistics warehouse. However, the method's dependency on the decisions gathered from experts might present some subjectivity, which could impact its application in other environments.

Bhatia *et al.,* (2020) proposes a network selection scheme for cognitive radio enabled WBANs using MADM methods. It evaluates different weighting methods and finds fuzzy AHP weights method performs well. The scheme adapts to changing network conditions, such as busy hours, and selects the best network for various data traffics. The paper suggests extending the scheme to handle incomplete information and exploring game theory applications.

In a bid to select the ideal IPS in a shipyard environment, the authors in (Cil *et al.*, 2021) combined FAHP and Fuzzy TOPSIS MCDMs. The criteria determined from literature was assessed using FAHP, while Fuzzy TOPSIS was used in ranking the alternative technologies. Simulation results demonstrated a ranking of the IPS at the shipyard. Although, the approach was the subjective nature of decisions in AHP and the limitation of the model in application to other indoor environments.

The work of (Hadi & Abdullah, 2022) proposed a combined MCDM approach that spliced MEREC and TOPSIS to identify the ideal location of urban hospitals caring for COVID-19 patients in Baghdad, Iran. The authors used MEREC to compute the weights of the selected criteria, while TOPSIS was used to rank alternatives. The work was done in two parts, the first was hardware dependent to obtain coordinate of regions, which was uploaded via the web to a designated database. The second part used a web application to feed in the alternatives and criteria to the system to identify the optimal location in the selected urban environment for COVID-19 patients. However, the model had potential scalability issues and the model likely needed more alternatives to increase the applicability of the model for urban context.

The work of (Cil *et al.*, 2022) presented a combined MCDM model that aided in selecting an ideal technology for different indoor scenarios in a shipyard environment. The authors spliced AHP and PROMETHEE to rank selected RF-based technologies used for IPS based on selected criteria. The authors used AHP to develop the localization framework, and then applied PROMETHEE to improve the sensitivity analysis. Both MCDMs spliced together were adopted to present a ranking of the RF-based technologies used for IPS. The drawback of the approach was the subjective nature of decisions in AHP and the limitation of the model in application to other indoor environments.

The work of (Bin Azim *et al.*, 2024) proposed q-spherical fuzzy sets to improve the process of making decisions in environments by considering four criteria and four alternatives. The authors evaluated the alternatives by incorporating the aforementioned approach with lower set approximation, upper set approximation, and a parameter q. The authors combined q-spherical approach with TOPSIS to

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expand its application in multiple environments. The performance improved decision-making against existing methods. The drawback of the approach was the large parameter tuning and the computational cost that may impact its application in real-time.

Ali *et al.,* (2024) put forward a fuzzy-logic-based cluster head selection approach for multipath routing in Wireless Sensor Networks (WSNs). The method efficiently distributes load, minimizes control message transmission, and ensures reliable routing. Simulation results show improved performance in energy consumption, active nodes, message delivery, load balancing, and system durability compared to existing algorithms. The proposed method is practical, scalable, and suitable for stationary homogeneous WSNs.

The approaches reviewed from the literatures primarily suffered from computational costs and decision bias, which could affect its application in other indoor localization environments. Hence, the need for approaches that are flexible. At this stage of this work, the authors of this work propose an approach with ubiquitous applications for indoor localization. The subsequent sections discuss the development of this proposed approach with a streamlined application to Wi-Fi.

METHODOLOGY

The focus of the proposed model is to improve the accuracy, precision, and efficiency of indoor positioning systems. On this premise, the model proposed a model that splices Simple Additive Weight (SAW) and Fuzzy Analytic Hierarchy Process (FAHP), which are both Multi Criteria Decision-Making (MCDM) schemes to achieve the goals aforementioned. Both MCDMs are well known from literature (Bin Azim *et al*., 2024; Budak *et al*., 2020; Budak & Ustundag, 2015; Cil *et al*., 2021; Cil *et al*., 2022). Discussed in the following subsections are the steps implemented in developing the proposed model.

Integration of SAW for Initial Alternatives

The integrations is implemented in six steps as delineated hereunder:

Step 1: Identifying Criteria and Alternatives

The SAW scheme is described as the simplest scheme amongst the existing MCDMs and it is obtained from average assigned weights. The SAW scheme computes the score for each alternative by performing product operations on the normalized decision matrix and allocated weights of importance. After the weighted products of the alternatives are compared, the final ranking of the alternatives is determined by rating them in order of preference. For this work, the alternatives are the configurations for deploying APs within indoor environments. The procedures hereunder are adopted in performing SAW:

Given a decision matrix problem, A, the set of b alternatives, which are the potential AP configurations within the indoor environment is denoted as:

$$b = (b_1, b_2, \dots, b_m) \qquad (1)$$

The set of criteria, z, denotes the application requirement. The requirements adopted for this paper are accuracy, precision, latency, signal strength, and signal management.

$$z = (z_1, z_2, \dots, z_m) \qquad (2)$$

A representation of the MCDM problem is characterised as:

$$D = (b \times z) \qquad (3)$$

Where D signifies the decision matrix, b represents the potential AP configurations within the indoor environments, and z, represents the application requirements.

Step 2: Constructing the decision matrix

For the decision matrix, rows characterize the potential AP configurations within the indoor environment, which are the alternatives, while the column denotes a criterion. The elements of the matrix represent the performance of the considered alternatives according to each criterion.

$$D = \begin{array}{c} z_o \\ b_1 \\ b_2 \\ \vdots \\ b_3 \end{array} \begin{array}{c} \begin{array}{cccc} z_1 & z_2 & \cdots & z_n \end{array} \\ \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \end{array} \qquad (4)$$

Step 3: Normalizing the Decision Matrix

The decision matrix is normalized to ensure that the considered criteria are comparable. As such, maximum and minimum value in each column is used to normalize the benefit criteria and cost criteria, respectively. A representation of benefit criteria is delineated hereunder:

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$$\bar{D}_{ij} = \frac{x_{ij}}{max(x_{ij})},\ i = 1,2,\dots,m, \quad j = 1,2,\dots,n \quad (5)$$

where $max(x_{ij})$ denotes the criteria parameter, which is the maximum entry of the *j-th* column in **D**, while x_{ij} represents the performance score of the *i-th* alternative in terms of the *j-th* criterion.

In the same vein, for the cost criteria, the lower the values of this parameter, the better the values. These values are obtained using (6):

$$\bar{D}_{ij} = \frac{min(x_{ij})}{x_{ij}}, \quad i = 1,2,\dots,m, \quad j = 1,2,\dots,n \quad (6)$$

Where $min(x_{ij})$ signifies the minimum entry of the *j-th* column of **D**.

Step 4: Assigning Weights to Criteria

Equation (7) is used to assign weights to the considered criterion based on their importance.

$$w = \{w_1, w_2, \dots, w_n\} \quad (7)$$

Step 5: Calculating the Weighted Sum

This is obtained for each alternative by multiplying the normalized matrix by the weight vector and summing the results as shown in (8):

$$H_{SAW}^{i} = \sum_{j=1}^{n} w_j . D_{ij}, \quad i = 1,2,\dots,n \quad (8)$$

Step 6: Ranking Centred on the Highest Score

Here the alternatives centred on their weighted sum is used in ranking. As such, the alternative that has the highest score is selected as the optimal configuration. This can be represented as (9):

$$Q = maxH_{SAW}^{i} \quad (9)$$

Integration of Fuzzy Analytic Hierarchy Process to Improve Criteria Weights

The Fuzzy Analytical Hierarchy Process (FAHP) is an MCDM technique that was developed from the AHP. The traditional AHP was developed to analyse complex decisions with the goal of mimicking the behaviour of humans to carry out choices. These decisions are carried out in three layers, namely: target layer, criterion layer, and the alternatives layer. However, the drawback of the traditional AHP is that it assumes the actions implemented to be deterministic, which makes the AHP a non-practical technique in localizing users as environmental factors among other hurdles introduce uncertainties to the system. To address this uncertainty in AHP, fuzzy set theory is used to equip the AHP to account for this uncertainty. Hence, the FAHP which was developed to adapt the conventional AHP model to practical environments. In the case of this work, it accounts for the fluctuations that may introduce outliers and errors to the data garnered and improves the localization criteria in identifying users indoors. Fuzzy largely aids in handling these fluctuations in data definitions. The approach introduces a range of values between [0, 1], which is the crisp logic found in the AHP.

Step 1: Constructing Fuzzy Pairwise Comparison Matrix

This step starts with gathering inputs to build a pairwise comparison matrix. Each element is a fuzzy number that characterizes the relative importance of one criterion relative to another as shown in (10).

$$\mu_M(x_{ij}) = \begin{cases} \frac{x_{ij}-I_{ij}}{m_{ij}-I_{ij}} & I_{ij} \le x_{ij} \le m_{ij} \\ \frac{x_{ij}-u_{ij}}{m_{ij}-u_{ij}} & m_{ij} \le x_{ij} \le u_{ij} \\ 0 & x_{ij} < 1 \ or \ x_{ij} > u_{ij} \end{cases} \quad (10)$$

These fuzzy numbers are characterized as Triangular Fuzzy Numbers (TFN), defined by (l, m, n), where l is the lower bound, m is the intermediate bound, and u is the upper bound. The fuzzy pairwise comparison matrix is delineated in (11):

$$\widetilde{D} = \begin{array}{c} z_o \\ b_1 \\ b_2 \\ \vdots \\ b_3 \end{array} \begin{array}{c} \begin{array}{cccc} z_1 & z_2 & \cdots & z_n \end{array} \\ \begin{bmatrix} (1,1,1) & (l_{12}, m_{12}, u_{12}) & \dots & (l_{1n}, m_{1n}, u_{1n}) \\ (l_{21}, m_{21}, u_{21}) & (1,1,1) & \ddots & (l_{2n}, m_{2n}, u_{2n}) \\ \vdots & \vdots & & \vdots \\ (l_{n1}, m_{n1}, u_{n1}) & (l_{n2}, m_{n2}, u_{n2}) & \dots & (1,1,1) \end{bmatrix} \end{array} \quad (11)$$

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Step 2: Normalizing the Fuzzy Comparison Matrix

The normalization process involves dividing each fuzzy element by the sum of the corresponding column. The goal of which is to achieve a form where the sum of each column is 1. For the fuzzy pairwise comparison matrix, $\widetilde{D}$, the sum of the fuzzy numbers is obtained using (12):

$$\widetilde{SM}_j = \left(\sum_{i=1}^{n} l_{ij}, \sum_{i=1}^{n} m_{ij}, \sum_{i=1}^{n} u_{ij}\right) \quad (12)$$

Each element of $\tilde{d}_{ij}$ in the fuzzy pairwise comparison matric is normalized as shown in (13):

$$\tilde{d}_{ij} = \left(\frac{l_{ij}}{u_{sm_j}} \frac{m_{ij}}{m_{sm_j}} \frac{u_{ij}}{l_{sm_j}}\right) \quad (13)$$

where the values of the denominator in (13), that is, u_{sm_j}, m_{sm_j}, and l_{sm_j} denotes the upper, middle, and lower bounds of the sum of the j^{th} column, respectively.

Step 3: Defuzzifying the Criteria Weights

The centroid method is used to convert the fuzzy numbers into crisp scores to obtain a value that represents the value of each criterion. This is shown in (14):

$$A_{crisp} = \begin{bmatrix} 1 & a_{12} & \dots & a_{1n} \\ a_{21} & 1 & & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & 1 \end{bmatrix} \quad (14)$$

Step 4: Calculating the Criteria Weights

The standard weights in this step are obtained by averaging the normalized values in each row of the matrix. This method presents a direct approach to determine the relative importance of each criterion. Equation (15) reflects the ubiquitous importance of the final weights assigned.

$$w_i = \frac{1}{n}\sum_{j=1}^{n} A_{crisp}(i,j) \quad (15)$$

Step 5: Consistency Check

This step ensures that the pairwise comparisons are consistent. To achieve the aforementioned, the Consistency Ratio, which is obtained by using the Consistence Index (CI) is computed and compared to the Random index (RI) as in (16). CR values that are used have values less than 0.1 (i.e., $CR < 0.1$) is used, but for CR values above the threshold (i.e., $CR \geq 0.1$), the pairwise value is revised to address inconsistency.

$$\lambda_{max} = \frac{1}{n}\sum_{i=1}^{n}\left(\sum_{j=1}^{n}\frac{a_{ij}w_j}{w_i}\right) \quad (16)$$

$$CI = \frac{\lambda_{max} - n}{n-1} \quad (17)$$

$$CR = \frac{CI}{RI} \quad (18)$$

Step 6: Re-evaluating the Weighted Sum with Improved Weights and Ranking of Alternatives

Recalculating the weighted sum of each alternative improved the weights obtained via FAHP. The re-evaluation makes sure that the examination of alternatives takes appropriate account of the updated criterion weights, which is used in the ranking of alternatives This is achieved using (19):

$$H_{SAW}^{i} = \sum_{j=1}^{n} w_j . D_{ij}, \qquad i = 1,2,\dots,n \quad (19)$$

The combination of the SAW and FAHP techniques is proposed to aid in a better informed decision-making Wi-Fi based indoor localization systems to improve the accuracy, precision, and efficiency of localization outcomes.

For analysis, MATLAB R2023a running on Hp Intel ® Core ™ i5-2520M CPU was used to analyze the data gathered. The simulation parameters are presented in Table 1.

Table 1: Simulation Parameters

Parameter	Value
AP Transmission Power (TP_{AP})	20dBm
Criteria Weights	[0.4, 0.3, 0.2, 0.1, 0.1]
Indoor Dimensions	$100m \times 100m$
Localization Threshold Error	1m
Noise Level	-90dBm
Number of APs (N_{AP})	10
Number of UEs (N_{UE})	50
Path Loss Exponent	3

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RSSI Sampling Rate	1 sample/second
Simulation Duration	86,400 seconds
Particle Initialization	Random within 10m
Particle Filter Step	Prediction, update, resample
Weight update method	RSSI likelihood
Resampling Method	Weighted Resampling

Performance Metrics

The following performance metrics are considered in this paper.

Average Localization Error

This metric presents the computes the average distance between the true and estimated positions of UEs. This is necessary to determine the localization accuracy in the Wi-Fi system. This can be obtained using (20).

$$Average\ Localization\ Error\ (ALE) = \frac{1}{N}\sum_{i=1}^{N}\sqrt{(x_i-\hat{x}_i)^2+(y_i-\hat{y}_i)^2} \quad (20)$$

where N represents the total number of UEs, (x_i, y_i) both characterize the true positions of the i^{th} UE, and $(\hat{x}_i, \hat{y}_i)$ both signify the estimated position of the i^{th} UE.

Precision

As applied to Wi-Fi-based localization, this metric denotes to variability or consistency of the localization error. The Standard Deviation (SD) of the localization errors is obtained using (21):

$$Precision = \left(\frac{1}{N}\sum_{i=1}^{N}\left(\sqrt{(x_i-\hat{x}_i)^2+(y_i-\hat{y}_i)^2} - ALE\right)^2\right)^{\frac{1}{2}} \quad (21)$$

Latency

This metric processes RSSI samples per unit time as the position of UEs are estimated. This can be determined using (22):

$$Latency = \frac{1}{RSSI\ Sampling\ Rate} \quad (22)$$

Mean Signal Strength

This metric is the average RSSI value that is logged by UEs from the APs. The logged values are used to determine the ubiquitous quality of the signal in the environment of interest as shown in (23).

$$Mean\ Signal\ Strength\ (SS_m) = \frac{1}{N \times M}\sum_{i=1}^{N}\sum_{j=1}^{M} RSSI_{ij} \quad (23)$$

where M represents the number of APs and $RSSI_{ij}$ characterizes the RSS from the j^{th}AP to the i^{th} UE.

Interference Management

This metric is evaluated by measuring the variance in RSSI values. The stability of the signal and the degree of interference due to environmental factors can be obtained using (24):

$$RSSI\ Variance = \frac{1}{N \times M}\sum_{i=1}^{N}\sum_{j=1}^{M}\left(RSSI_{ij} - SS_m\right)^2 \quad (24)$$

RESULTS

Figure 1 illustrated the Wi-Fi-based indoor localization map utilized for this research. The performance of the proposed model was tested on the simulation environment using the simulation parameters presented in Table 1. Figure 2 to Figure 4 presents the distribution of localization errors, performance values of the performance metrics, and the distribution of signal strength.

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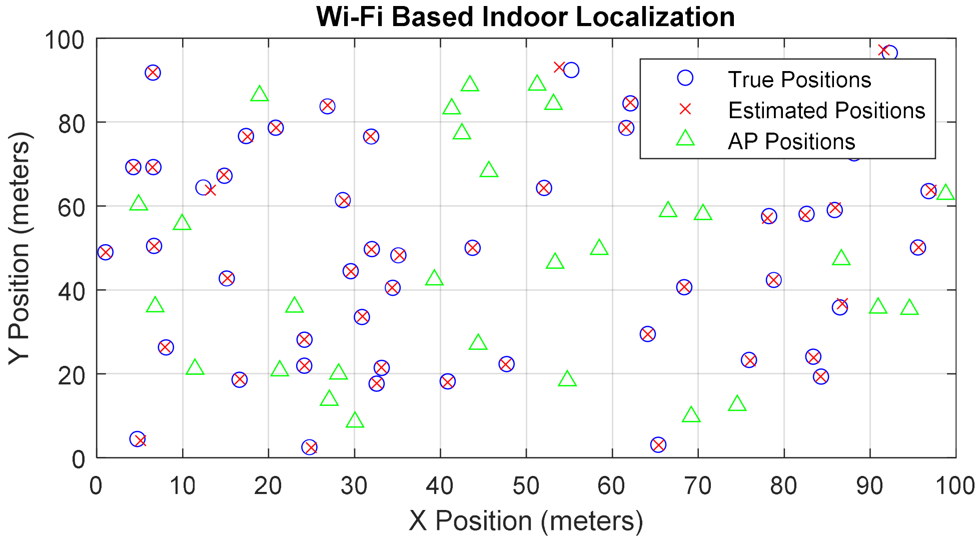

Figure 1: Wi-Fi Based Indoor Localization Map

The area of this floor in Figure 1 is $1000m^2$. The number of Wi-Fi APs (N_{AP}) considered is 10, while the number of UE (N_{UE}), whose true position are measured and its estimates that are obtained from RSSI values is 50. The Wi-Fi APs have a Transmission Power (TP_{AP}) of 20dBm. The discussion for the remaining output that is of Figure 2 to Figure 4 are discussed in section 6.

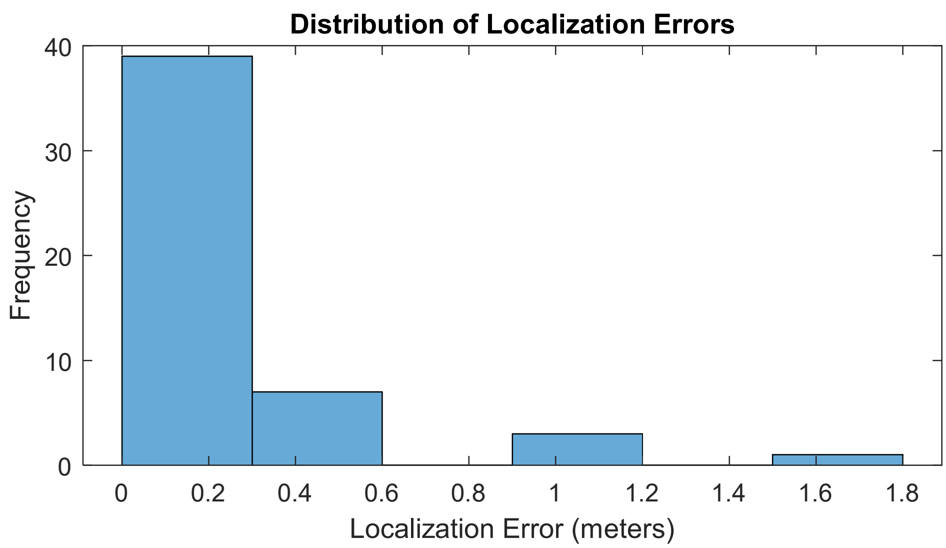

Figure 2: Distribution of Localization Errors

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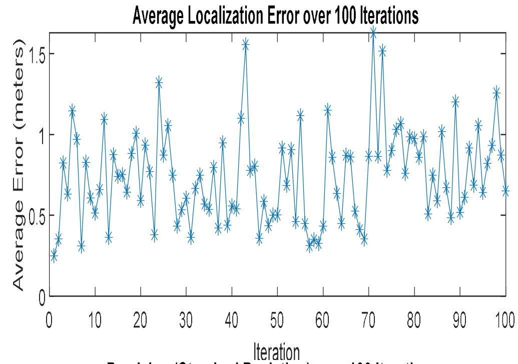
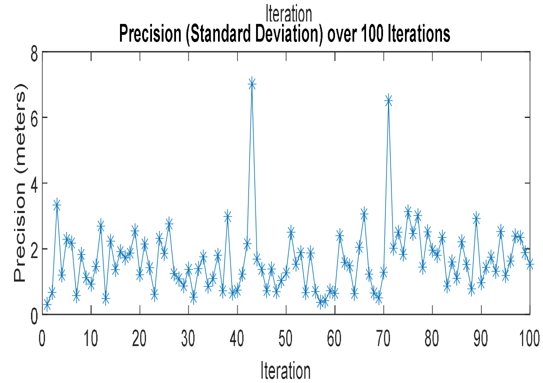
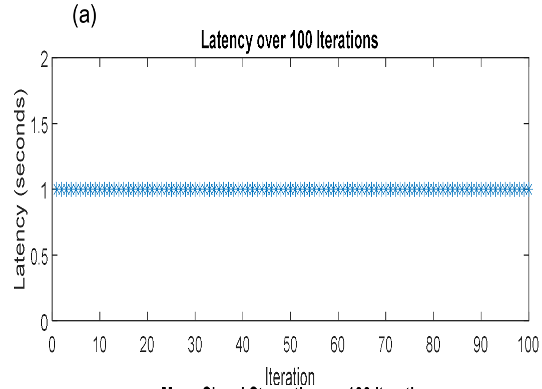
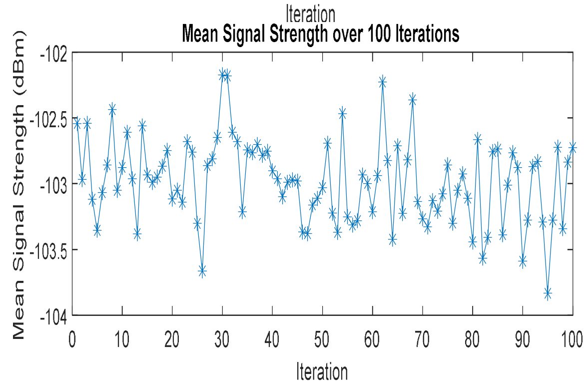




(a) (b)





(c) (d)

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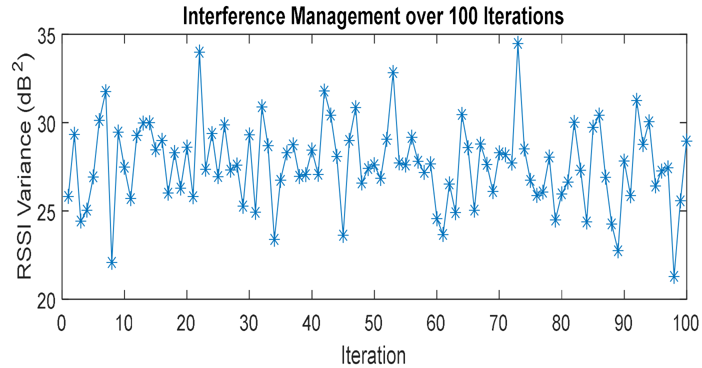

(e)

Figure 3: Performance Metrics after 100 Iterations (a) Average Localization Error (b) Precision (c) Latency (d) Signal Strength (e) Interference Management

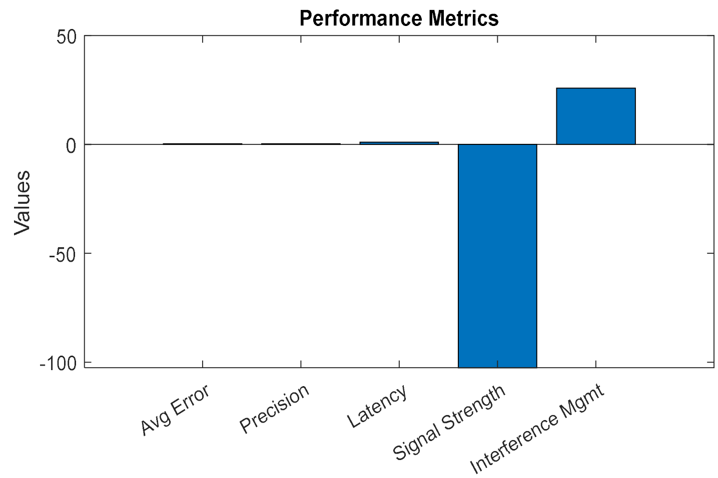

Figure 4: Average Performance Values of the Performance Metrics

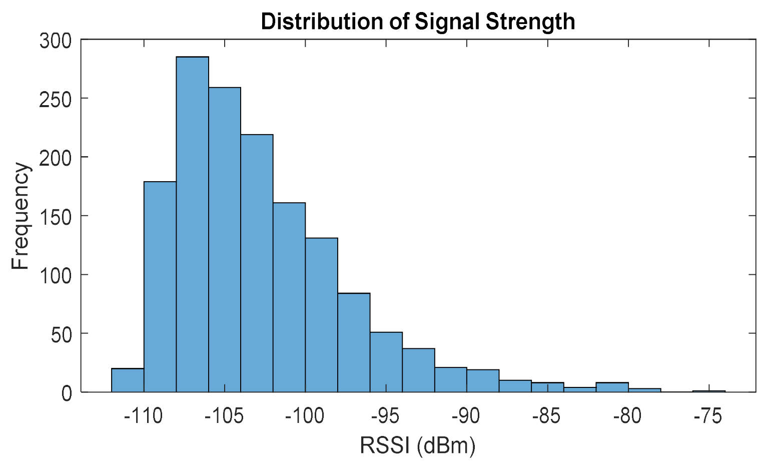

Figure 5: Distribution of Signal Strength

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Table 2 presents the localization performance metrics.

Table 2: Localization Performance Metrics

Performance Metrics	Output
Average Localization Error	0.25m
Precision (Standard Deviation)	0.30m
Latency	1sec
Mean Signal Strength	-102.54dBm
Interference Management (RSSI Variance)	25.82dB^2

DISCUSSION

The values of all the metrics were dependent on the estimated position of the UE in relation to the true position of the UE and the AP's position. As such, the value of the performance metrics in each estimated position of the UEs which was random with each run after every 100 cycles was observed to differ slightly. In this paper, one of the outputs was randomly selected for one of random scenarios of the output as all outputs showed efficient indoor positioning results for the metrics considered. Delineated hereunder are the discussions for the outputs.

Average Localization Error

Figure 2 shows the distribution of localization error with the average localization error over 100 iterations in Figure 3a. The model achieved a 25cm deviation from the true coordinates and the estimated coordinates of the UEs. The deviation between the true coordinate of the UEs and their estimated coordinates is largely influenced by the true and estimated coordinates of the UEs, which can be calculated using (20). This metric is vital to the accuracy of the indoor positioning of UEs. Generally, the lower the average localization error the higher the accuracy of the localization model for indoor positioning, and vice versa is the case for average localization errors that are high. In this case, the proposed model achieved a centimetre-level of accuracy, hence, making it important for indoor positioning localization.

Precision

The performance consistency of the proposed localization model is illustrated in Figure 3b. This represents the SD from of localization errors. Equation (21) was used in computing the SD of the values represented in Figure 3b. As illustrated in Figure 4 and Table 2, the average performance value of the precision over 100 iterations achieved an SD of 30cm. This represents the variability in localization errors. Generally, the smaller the SD, the closer the localization error to the mean error, which characterizes the models reliability and stable performance, as shown with the results obtained for this study.

Latency

The values of the several performance metrics are illustrated in Figure 3c. The observed latency is 1 second. This represents the RSS sampling rate of 1 sample per second, which is obtained using (22). Generally, the lower the latency the better the responsiveness of the model in logging the coordinates of a UE, and the inverse is the case when the latency is higher. In the same vein, the latency influences the effectiveness of the model in real-time indoor positioning.

Mean Signal Strength

Figure 3d presents the value used in representing the signal strength value over 100 iteration. As represented in Figure 4 and Table 2, a mean signal strength of -102.54dBm was achieved. Although, this is relatively low, due to the dynamic factors and nature of the environment, the

Interference Management

Figure 5 showed that the signal quality in the simulation environment is left-skewed distributed. However, its values gradually approaches the centre of its axis with an RSSI variance of 25.82dB^2. This suggests that the interference is moderate with causes such as electronic devices and obstacles from the environment, which is dynamic. The values obtained are computed using (24).

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CONCLUSION

This research presents the preliminary results of a proposed model that utilizes a combination of SAW and FAHP to improve the indoor positioning. On this premise, the analysis presented are centred on five performance criteria, which are accuracy, precision, latency, signal strength, and interference management. At this stage of the research, SAW was used to develop the infrastructure to test different dynamic environmental scenarios. This was further spliced with FAHP, which modified the weights assigned the aforementioned criteria in order to mitigate deviations and achieve better indoor positioning results. Simulation results showed that the model achieved an average localization error of 25cm with a standard deviation of 30cm, which shows the models applicability in indoor settings. Alongside the mean signal strength and RSSI variance, the proposed model showed an adaptability an indoor positioning scheme. In addition to the aforementioned observations, it was observed from interference management, which reflected the variance in RSSI values that the model can become more robust by utilizing time analysis and other clustering techniques, which will be considered for future works. This is expected to further improve accuracy, precision, and improve the mean signal strength of the proposed localization and strengthen its efficiency for indoor positioning applications. Additionally, a comparison of the approach would be carried out against other RF-based technologies that localization systems are built atop.

Definition of Terms

This section presents the full definition of terms adopted in this paper.

Terms	Definitions
N_{AP}	Number of APs
N_{UE}	Number of UEs
TP_{AP}	AP Transmission Power
ALE	Average Localization Error
AP	Access Point
FAHP	Fuzzy Analytical Hierarchy Process
IPS	Indoor Positioning System
IVIF	Interval-Valued Intuitionistic Fuzzy
MCDM	Multi-Criteria Decision Making
RSSI	Received Signal Strength Indicator
RTLS	Real-Time Location Systems
SAW	Simple Additive Hierarchy
SD	Standard Deviation
TFN	Triangular Fuzzy Numbers
UE	User Equipment
Wi-Fi	Wireless Fidelity

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