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Original scientific paper

Enhancing Wi-Fi Router Placement with Unsupervised Machine Learning for Improved Network Coverage and Performance

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Abstract: The optimal placement of Wi-Fi routers is essential for ensuring strong and consistent wireless coverage, yet traditional approaches often fail to deliver comprehensive solutions. This study presents a novel application of unsupervised machine learning (ML) to improve Wi-Fi router placement by analyzing environmental factors, historical signal strength data, and user behavior patterns. Using a dataset of signal strength measurements from a multi-story building, we conducted feature engineering to identify key predictors and trained various ML models to predict the impact of router placement on signal performance. The models were assessed based on accuracy, robustness, and computational efficiency. Our results show that ML-driven placement strategies significantly reduce dead zones and enhance overall network performance. Moreover, the proposed approach streamlines the installation process and supports adaptive, real-time adjustments to changes in the environment or usage patterns, offering a scalable solution for modern network infrastructure. These findings have practical implications for network engineers and set the stage for future innovations in intelligent network design and optimization.

Keywords: Wireless network, Wi-Fi, Optimization, Router placement, Machine learning, Signal strength.

1 Introduction

In today's world, where connectivity is more essential than ever, ensuring efficient and robust Wi-Fi coverage is of paramount importance. As a critical

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Colour versions of the one or more of the figures in this paper are available online at https://sjee.ftn.kg.ac.rs component of digital communication infrastructure, Wi-Fi networks support numerous online activities, including high-definition video streaming, real-time video calls, and extensive data transfers. These networks serve as lifelines in both personal and professional realms, maintaining virtual connectivity globally. The integration of 5G networks with indoor navigation systems significantly improves the optimization of Wi-Fi router placements for drone navigation in complex indoor environments [1, 2]. While achieving optimal Wi-Fi coverage across diverse settings remains a major technical challenge, it is a crucial one that demands innovative solutions.

Wi-Fi signal quality is significantly influenced by factors such as room layout, construction materials, and interference from other electronic devices [3, 4]. These factors can create areas with poor or no coverage, known as 'dead zones. In business settings and during critical communications, dead zones can cause substantial disruptions, directly impacting productivity and user experience. The limitations of traditional methods have prompted the exploration of more advanced, data-driven solutions [5].

Traditional methods for Wi-Fi router placement often rely on trial-and-error or rule-of-thumb approaches, which are inherently imprecise and inefficient. These methods typically fail to account for the complex interplay of environmental factors, such as varying room layouts, diverse construction materials, and the presence of electronic devices that cause interference. Consequently, this can lead to suboptimal coverage with persistent dead zones and areas of weak signal strength [6]. Additionally, traditional approaches lack the adaptability to respond to dynamic changes in the environment or user behavior, resulting in a static network configuration that may not meet evolving connectivity demands. These limitations highlight the need for more sophisticated, data-driven solutions that can optimize Wi-Fi coverage in a systematic and responsive manner.

The adoption of ML solutions offers an unprecedented approach to solving these challenges. ML, a subset of artificial intelligence, enables computer systems to learn and enhance decision-making by independently analyzing data patterns. When applied to Wi-Fi router placement, ML can analyze extensive datasets encompassing environmental characteristics, user density, and other relevant features, thereby predicting the optimal router locations to enhance coverage quality and reduce interference [7]. These ML models process vast amounts of data to identify intricate patterns, facilitating the precise positioning of Wi-Fi routers for superior network performance.

In this paper, we concentrate on the implementation of supervised learning techniques which employ labeled datasets for training algorithms to recognize efficient patterns in router placement. The goal of this research is to show how sophisticated ML methods can be utilized to handle Wi-Fi router placement complexity, thereby improving network connections and performance across different surroundings. The tools generated from the insights will empower network engineers and data scientists with the necessary skills to enhance the infrastructure connectivity and deploy the Wi-Fi network effectively to address the digital society's demand.

This paper is structured as follows: Section 2 presents some studies about the optimal placement of Wi-Fi routes. In this section many solutions, which have been presented in literature, will be discussed. Section 3 presents the methodology of our study. We will start by presenting the used dataset. Then, processing of dataset will be given. Finally, feature engineering and data clustering will be illustrated in this section. Study results will be given at Section 4 with discussion. Finally, the paper will be concluded in Section 5.

2 Literature Review

The optimal placement of Wi-Fi routers remains a core challenge in indoor wireless network design, particularly due to the complex spatial variability of radio propagation in buildings. Traditional methods, such as manual site surveys and heuristic placement rules, are widely used but frequently produce suboptimal coverage and persistent dead zones because they do not capture environmental dynamics or user-driven variations in signal demand. Recent studies highlight these limitations and emphasize the need for data-driven or algorithmic approaches that can adapt router placement to indoor conditions more accurately [5, 7].

ML techniques have been increasingly applied to improve indoor Wi-Fi performance, especially through the prediction of signal strength maps and user connectivity patterns. Supervised regression models such as Gaussian Process Regression (GPR) and ensemble methods have shown strong capability in modeling RSSI distributions under varying environmental conditions [11−13]. These models reduce the reliance on extensive manual calibration and help identify areas requiring improved coverage by capturing nonlinear relationships between obstacles, distance, and signal attenuation. For instance, authors of [5] involve improving Wi-Fi fingerprinting for indoor localization where GPR is used to increase signal strength prediction accuracy and lower the number of manual calibration efforts. Through manipulating a sophisticated kernel function, this enhanced GPR model is capable of the handling the variabilities of indoor signal strength affected by environmental factors. This technique drastically lowers the localization error, which translates into more accurate Wi-Fi signal distributions prediction and, as a result, to better placement and performance of Wi-Fi access points.

In parallel, a significant body of work explores optimization-based placement of Wi-Fi access points. Meta-heuristic algorithms (including Genetic

Algorithms, Particle Swarm Optimization, and Simulated Annealing) have been shown to provide effective solutions for balancing coverage, interference, and deployment cost in indoor networks [14−16]. These methods evaluate candidate configurations based on predicted signal maps or objective functions such as coverage percentage or overlap minimization. More recent approaches combine ML and optimization, where ML-derived signal models guide search algorithms toward more promising placement configurations.

Complementary work on RSSI-based localization and fingerprinting also informs router placement research, as the same propagation characteristics that influence localization accuracy affect coverage planning [14]. Enhanced RSSI modeling techniques, multilateration approaches, and hybrid ML-vision methods contribute insights into spatial signal behavior and help refine the understanding of how router placement affects network performance. For instance, in [7] on robust Wi-Fi localization proposes DIFMIC. It is a framework that uses derivative RSS fingerprints fusion with multiple classifiers to increase localization accuracy in a dynamic environment. Consequently, DIFMIC uses a two-layer fusion profile joint optimization algorithm, which takes the best of different classifiers and thus improves the accuracy of prediction. This method includes hyperbolic location fingerprints and signal strength difference fingerprints which are processed with a ML classifier like K-nearest neighbors and Random Forest. DIFMIC leverages the synergies of multiple kinds of data to adjust it to different scenarios and keeps recalibration to a minimum, highlighting multiple advances in comparison to the RSS-based techniques and achieving impressive outcomes in the actual tests of localization.

Together, these studies demonstrate a clear shift toward learning-based and optimization-driven models for improving Wi-Fi deployment [17, 18]. However, existing approaches often require high-fidelity measurement campaigns or computationally expensive simulations, creating a need for lightweight, data-driven frameworks that can operate using available signal measurements while maintaining practical applicability [19, 20]. The present work builds on this gap by exploring ML-supported analysis of indoor RSSI distributions to inform and refine router placement decisions.

3 Methodology

This section outlines the methodology employed in the study, which encompasses data collection, data preprocessing, feature engineering and data clustering. Each of these steps is crucial for building an effective ML model to optimize Wi-Fi router placement. The process begins with comprehensive data collection, capturing signal strength measurements and environmental variables from the multi-floor educational building. Following this, data preprocessing is conducted to clean and normalize the data, ensuring its suitability for analysis.

Feature engineering is then performed to extract relevant predictors that influence Wi-Fi signal quality, such as room layout, construction materials and user density. Finally, data clustering techniques, specifically K-means clustering, are applied to identify optimal router locations by grouping areas with similar signal characteristics. This systematic approach aims to enhance signal coverage and minimize interference, ultimately improving network performance.

3.1 Data collection

The multi-floor indoor location-based Wi-Fi signal strength project data served as the initial dataset for the study on the optimization of the Wi-Fi router placement within the academic environment. The dataset had to be selected for the fact that it had enough coverage that stretched from different environmental conditions and diverse usage of the buildings structure to understand signal propagation in complex structures. The following figure 1 gives the structure of the building.

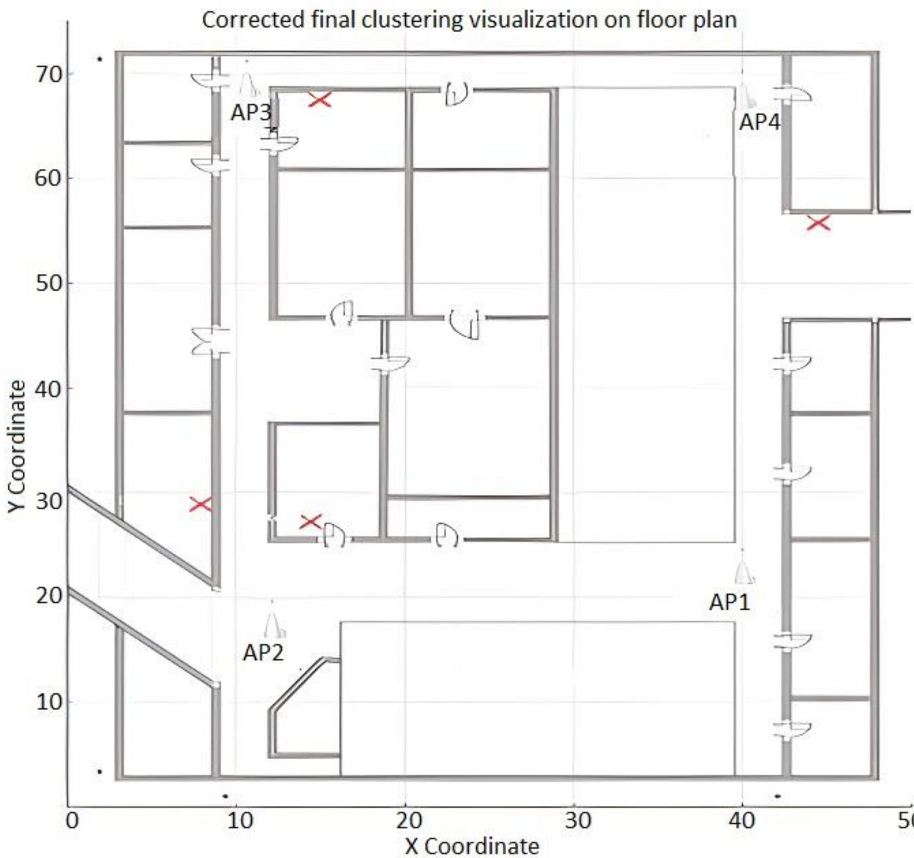

Fig. 1 – *Building structure.*

RSSI data from four Wi-Fi access points situated at different points within the building are contained in this dataset [9, 10]. A record has the RSSI value, spatial coordinates (x, y, z) and a sequence number of measurements as is shown in **Table 1.**

Table 1
Dataset overview.

Access Point	Coordinates	Number of Samples	Data Range
A	(23,17,2)	30,000	01-01-2007 to 31-01-2007
B	(23,41,2)	30,000	01-01-2007 to 31-01-2007
C	(1,15,2)	30,000	01-01-2007 to 31-01-2007
D	(1,41,2)	30,000	01-01-2007 to 31-01-2007

The data collection was carried out in all the accessible areas of the building which encompassed different room types and layouts as much as possible to capture most of the signal interference patterns and coverage issues. The data was collected through the course of one month, including peak and off-peak usage hours so as to have an even mix of the building's daily and weekly access patterns (see Fig. 2).

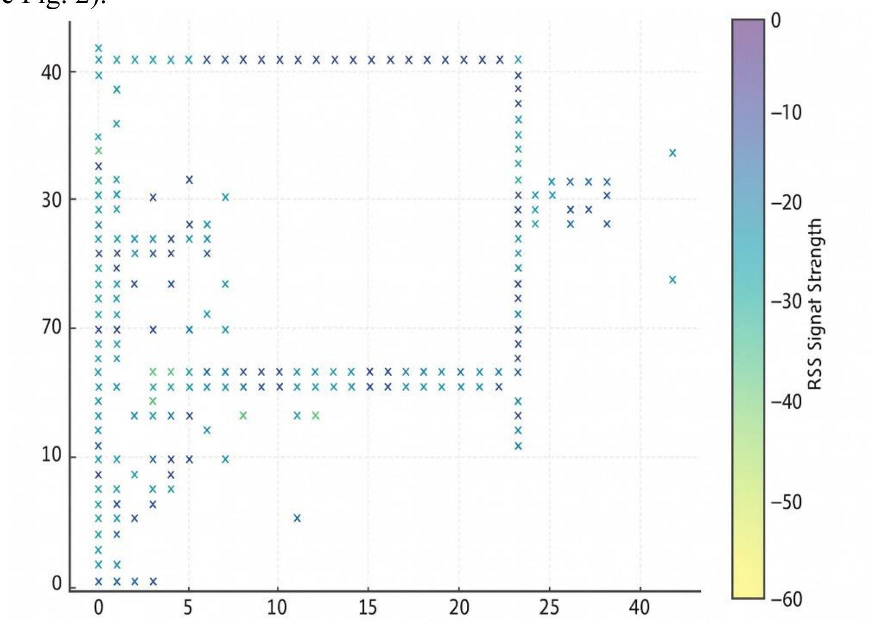

Fig. 2 – *Spatial distribution of RSSI Samples.*

To ensure the validity of the obtained dataset, several conditions were met to ensure the data's reliability and suitability for the objectives set in the study. This involved analysis of signals in terms of the degree of accuracy of the collected

RSSI values in relation to the actual spatial coordinates of the real building structure.

RSSI measurements were collected from a set of predefined reference points distributed across the indoor environment. Each reference point had known (x, y) coordinates, and the measuring device was positioned at a consistent height to ensure uniform propagation conditions. At every reference point, Wi-Fi scanning was initiated to detect all visible Access Points (APs) within range. For each detected AP, the MAC address (BSSID) and the corresponding RSSI value were recorded. Because RSSI values are subject to temporal fluctuations caused by multipath effects, interference, and environmental dynamics, multiple scans were performed at each reference point. These scans were taken consecutively with short time intervals to capture natural variability. The collected RSSI values for each AP were then aggregated (typically using the arithmetic mean or a truncated mean) to obtain a stable representative value for that location. The resulting fingerprint for each reference point consisted of the list of detectable APs and their aggregated RSSI values. This fingerprint was associated with the known coordinates of the reference point and stored in the dataset. The full set of fingerprints constituted the radio-map used for subsequent trilateration-based estimation of AP locations. Fig. 3 illustrates RSSI values by each access point.

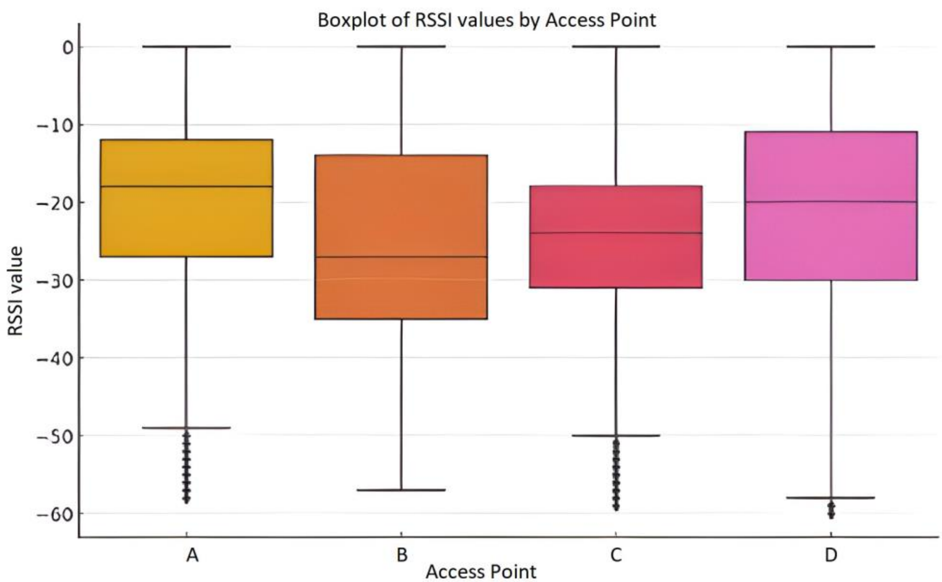

Fig. 3 – *RSSI values by each access point.*

The dataset used in this work was not originally accompanied by temporal metadata nor by explicit height (z-axis) metadata associated with each RSSI reading. As a result, no analysis is performed in our work with respect to sampling frequency over different periods (day/night or workday/weekend) or variation in measurement height. This limitation is acknowledged, and the results are interpreted under the assumption that the provided RSSI readings correspond to a static measurement context without vertical variation.

3.2 Data preprocessing

To prepare the dataset for ML analysis, it underwent several preprocessing steps aimed at enhancing data quality and suitability for the applied ML techniques.

Before applying ML methods, a detailed rule-based cleaning procedure was performed. Data cleaning was carried out manually, without the use of ML models. Each entry was examined to identify incomplete records, duplicated samples, or values outside the expected RSSI operating range. Physically implausible RSSI values (such as measurements exceeding the sensitivity limits of the receiver or values inconsistent with the approximate distance from corresponding access points) were identified using threshold-based rules and subsequently removed. Entries containing missing AP identifiers, zero-strength readings not supported by any detected access point, or formatting inconsistencies were also excluded. When feasible, minor inconsistencies such as incorrectly formatted MAC addresses were corrected; otherwise, the affected records were discarded. **Table 2** summarizes the categories of removed or corrected records.

Table 2

Data summary after cleaning task.

Step	Records Before	Records After	Removed Records
Initial	120000	119967	33

The RSSI channel values were normalized to range between 0 and 100 by applying min-max normalization technique. They help to compare the data at different access points and also ensure compliance with standards that are used for the signal strength analysis:

$$\text{Normalized Value} = \frac{\text{Value} - \text{Min}}{\text{Max} - \text{Min}} \times 100 . \quad (1)$$

The collected data set was then spatially accumulated to obtain the average of signal strength in any geographic location. It reduces interference from noise and focuses more on signals that are fixed with strong trends in the environmental conditions.

Principal Component Analysis (PCA) was used to reduce the number of variables and maintain the key information. The PCA process was set up to retain components that at least account for 85% of the variation in the signal strength, and this allowed the reduced dataset to capture the main aspects of the signal strength across the building.

This manual rule-driven approach ensured that the resulting dataset contained only consistent and physically plausible RSSI observations prior to normalization, spatial aggregation, and PCA.

3.3 Feature engineering

Feature engineering is an essential component of the transformation of raw data into useful information for ML models. We developed several stages to improve and enrich the data set with characteristics, which describe the relevant factors effecting Wi-Fi signal strength and distribution in a multi-story building setup.

The dataset contains x, y and z coordinates valid for indicating the positioning of RSSI points in the building. These were normalized in order to have the same range of values in all x dimensions which in turn helped the distance-based calculations used in clustering to be more accurate. To normalize the coordinates, the min-max scaling was employed which scales the coordinates into the range between 0 and 1.

The obtained RSSI values depicting the received signal strength at various points were then averaged for a set of coordinates to minimize short term fluctuations and focus more on general signal trends. This averaging is crucial for revealing hot or cold spots that define the location of Wi-Fi routers because of signal coverage.

To account for this possible increase in device usage, the KDE method was used to compute the density of data points by location. This smoothed density metric enables us resolve hot zones that would need superior signal strength to support many users efficiently. Density of data points is estimated according to the following equation:

$$\hat{f}(x) = \frac{1}{nh} \sum_{i=1}^{n} K\left(\frac{x - x_i}{h}\right), \tag{2}$$

where, n is the number of data points, h is the bandwidth parameter (smoothing parameter), x_i are the data points, K is the kernel function, typically a probability density function that is symmetric around zero. The kernel function K determines the shape of the estimator around each data point x_i, and h controls the smoothness of the estimated density function $\hat{f}(x)$.

Different aspects of a building construction play major role in propagation of the signals such as layout and medium used in construction. As for the above issue, we added another option that calculates the signal strengths according to the presence of the types of materials between the access points and the points of measurement. These were obtained from the building plan and estimated using typical electrical industry values of the attenuation of the signal through different materials.

As for the usage of buildings during different periods of time, the information was divided into time slots and compared by mornings, afternoons, and evenings. To evaluate the fluctuations in signal performance with reference to daily usage patterns, the average signal strength for the structures was computed in relation to consecutive blocks of time. It is done in a temporal way, and that makes it possible to better plan the volume of capacities needed or the organization of the networks at certain moments.

3.4 Data clustering

To make the best choices regarding the places for every router and getting an idea of the area covered by distinct signal amplitude, the K-Means clustering algorithm was applied in this work. This method divides the data points, and puts them into different clusters which are related by how similar they are. In this case, similarity was defined as engineer factors such as signal strength, location density, and even environmental elements.

Number of clusters *k* was determined using the Elbow Method where various numbers of clusters with their WCSS values are plotted and the point where the reduction in the WCSS starts to be slow is determined. *k* was selected as 4 in this effort after moving average approach was applied on WCSS trend (see Fig. 4).

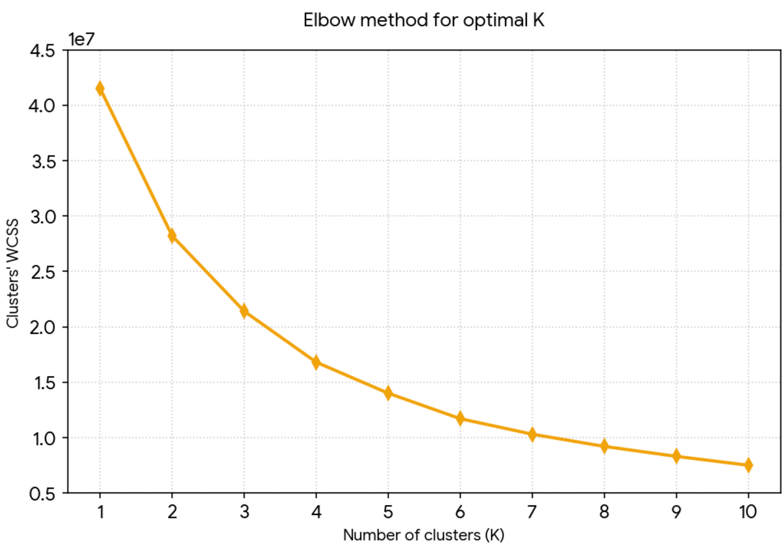

Fig. 4 – *Optimal number of clusters k based on Elbow method.*

The clustering algorithm was set to “k-means++” in which random selection of initial centroids is utilized for faster convergence and better clustering results. This method is especially helpful to prevent undesirable results of clustering such as random centroid initialization. Here's a simplified overview of the steps involved:

– Randomly select the first centroid from the data points.

– For each remaining data point x, calculate the distance $D(x)$ to the nearest, already chosen centroid.

– Select the next centroid from the data points with a probability proportional to $D(x)^2$.

– Repeat the second and the third step until k centroids are chosen.

In this work, the distance between data points during clustering was computed using the Euclidean distance metric, consistent with the standard K-Means formulation. All distance calculations were performed in the normalized RSSI feature space, ensuring that each RSSI dimension contributed equally without additional weighting. When centroids were updated during the iterative K-Means process, the same Euclidean metric was applied to assign each point to the nearest centroid. No kernel functions, feature weights, or alternative distance measures were used.

The distance $D(x)$ is calculated as:

$$D(x) = \min_{c \in C} x - c^2, \tag{3}$$

where C is the set of already chosen centroids.

This initialization helps in finding clusters that are more naturally separated, leading to better convergence and often better overall results.

The data was clustered using the K-Means algorithm with $k = 4$, as determined from the Elbow Curve. The quality of the resulting clusters was evaluated using silhouette scores, which measure how well each data point fits within its assigned cluster compared to other clusters. High average silhouette values were obtained for all four clusters, indicating good compactness and clear separation between groups. A summary of the silhouette value for each cluster is presented in **Table 3**, and Fig. 5 illustrates the final cluster distribution. These results confirm that the clustering structure is meaningful and that the applied K-Means configuration produced a high-quality grouping of the data.

The last clustering was presented in the form of the figure that depicted the centroids as well as the geographical location in reference to the floor plan (see Fig. 1). It is utilized here to provide better understanding of the features of router placements as concerning spatial efficiency.

4 Results and Discussion

This section gives the results of the study which was aimed at determining the most suitable places to install Wi-Fi routers in a multi-story academic facility. After the application of the proposed RSSI processing, we employed K-Means clustering to identify optimum location that gives the best signal strength and stability without the generation of interference or signal fading.

4.1 Clustering outcomes

The data was clustered using the K-Means clustering algorithm with $k = 4$, which was determined from the Elbow Curve. Thus, silhouette scores, which indicated high values for all clusters, confirmed the clustering process and once again proved that the algorithm successfully identified groups within the data. The silhouette values for each cluster were high, which shows that the clusters were well separated and compact which confirms that our clustering solution is of high quality. Fig. 5 presents the clusters. **Table 3** gives a summary about each cluster. To quantitatively evaluate the clustering quality, the average silhouette score was computed for each cluster, along with the overall mean silhouette score. As shown in **Table 3**, all clusters exhibit positive silhouette values, indicating good separation and cohesion. The overall silhouette score further confirms the robustness of the selected K-Means configuration ($k = 4$).

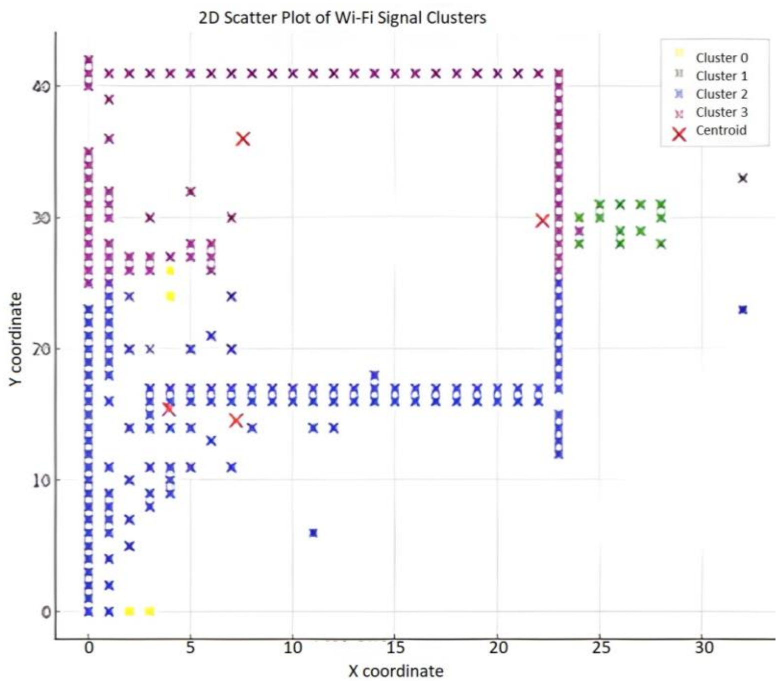

Fig. 5 – *WiFi signal cluster.*

Table 3
Summary of each cluster.

Cluster	xCoordinate	yCoordinate	MeanSignal Strength	Signal Variance	Avg. Silhouette Score
0	3.93	15.42	-13.71	28.35	0.71
1	22.22	29.79	-13.97	54.48	0.64
2	7.22	14.56	-33.05	38.94	0.67
3	7.56	36.00	-29.12	68.72	0.60

For cluster 0, located close to the lower-central part of the building, this centroid has high signal levels and low variability. A router positioned here will help provide the most commonly used areas and hallways with strong Wi-Fi signals. Cluster 1 covers area which are likely near essential facilities or office spaces are located towards the upper right. High signal strength but high variance may suggest that the signal is fluctuating, and there is a presence of barriers that can cause the interference or improvement of signals. The position of the strategic router here could enhance local connectivity for the important activities as well as the high traffic zones. In addition, cluster 2 its centroid is situated to the right of Cluster 0, but as with many other clusters we have seen, it may be a different part of the building, perhaps on a lower floor or where signals are weaker and thus more homogenous, as may well be the case with storage areas. It would be important to place a router here to reinforce the network coverage in the less-covered areas and thus provide a more uniform network availability. Finally, cluster 3 its centroid indicates that the upper left area is close to transitional zones such as corridors or entry/exit areas. This moderate signal strength despite the higher variance also suggests ways to increase network reliability and service continuity in movement areas by improving the position of the routers. RSSI values by each cluster are represented in Fig. 6. Fig. 7 illustrates RSSI distribution for each cluster.

The findings of the cluster analysis provide the evidence-based guidelines of Wi-Fi routers location placement that guarantees both strong signal coverage and network stability in the multi-story academic building. The idea of installing routers at the particular centroid identified from the clustering process gives the following benefits:

1. Enhanced Signal Coverage: The location of routers in the middle of clusters ensures stability in transmission of signals within the central and peripheral areas. This approach essentially eliminates dead zones or areas with low signal strength and provides full coverage of the building.
2. Improved Network Stability: The variance in signal strength at the centroids shows that these locations have consistent and sufficient signal coverage. This minimizes signal loss and interference that is typical whenever users are in constant motion in the building.

3. Efficient Resource Utilization: When using the above clustering method, it is easier to determine where to position these routers so as to cover the largest area with the minimum number of routers. This focused positioning eliminates duplicate and overlapping use of network resources and technology.
4. Enhanced User Experience: By deploying routers in areas with high user concentration and strong signal fluctuations, the users enjoy superior and more stable Wi-Fi connectivity. This additional connection is especially useful in highly trafficked spaces like lecture halls, libraries, and common areas.

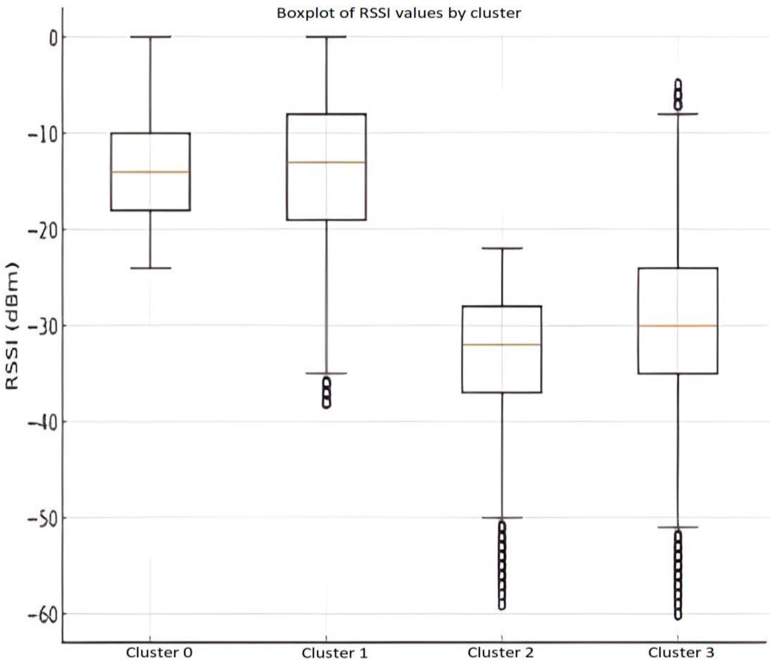

Fig. 6 –*RSSI values by each cluster.*

4.2 Discussions

The clustering analysis shows some key considerations for optimal router placement:

– Centralized Coverage: The deployment of routers near the centroid of Cluster 0, positioned at coordinates (3.93, 15.42), is essential for enhancing Wi-Fi coverage in moderately high-traffic areas adjacent to essential pathways. While this location is not the central-most point of the building, it is strategically significant for covering areas with consistent user activity, supporting both academic and administrative operations effectively.

– Peripheral Enhancement: The centroids identified in Cluster 1 at (22.22, 29.79) and Cluster 2 at (7.22, 14.56) represent critical areas on the periphery of the building. Enhancing Wi-Fi coverage in these locations is crucial for expanding the network's reach and improving connectivity in regions previously characterized by weaker signal strengths. This approach ensures a more comprehensive network coverage, encompassing all necessary areas of the building.
– Transition Zones: The centroid for Cluster 3, located at (7.56, 36.00), highlights the need for robust Wi-Fi coverage in transitional zones such as corridors and hallways. These areas are pivotal for maintaining uninterrupted connectivity as users navigate through different sections of the building. Strategic router placement in these zones ensures that connectivity is maintained seamlessly, enhancing user experience and operational efficiency.
– Adaptability to Environmental Factors: The clustering analysis considers the impact of environmental factors such as building materials and layout on Wi-Fi signal propagation. Strategic placement of routers at the determined centroids is crucial for mitigating potential signal degradation caused by structural impediments. This adaptability is particularly important in a multi-floor academic building where varied structural elements can affect signal dynamics, thereby enhancing the overall effectiveness and efficiency of the Wi-Fi infrastructure.

The potential of the proposed solution for Wi-Fi deployment in a dynamic and complex academic environment is further strengthened by a data-driven approach that strategically determines router locations based on evidence from real data. This approach guarantees that placements are not random but rather supported by signal strength and coverage studies, network stability tests, user density, and environmental surveys.

The average signal levels recorded at each cluster center show that the selected sites can support strong and reliable Wi-Fi connections. This is particularly useful in areas with heavy traffic or with significant structural interferences where a stable connection is crucial for continuous academic and administrative operations. The high signal strengths at these centroids indicate reliable internet connectivity within the building. In addition, the difference in the signal strength at each centroid indicates the stability of the network. But lower variance indicates that the signal strength doesn't change much and this is crucial for preventing connectivity instabilities from potentially interrupting user tasks. Through maintaining low variance at key points, the network has the potential for providing consistent and stable functionality, especially in environments with concurrent users.

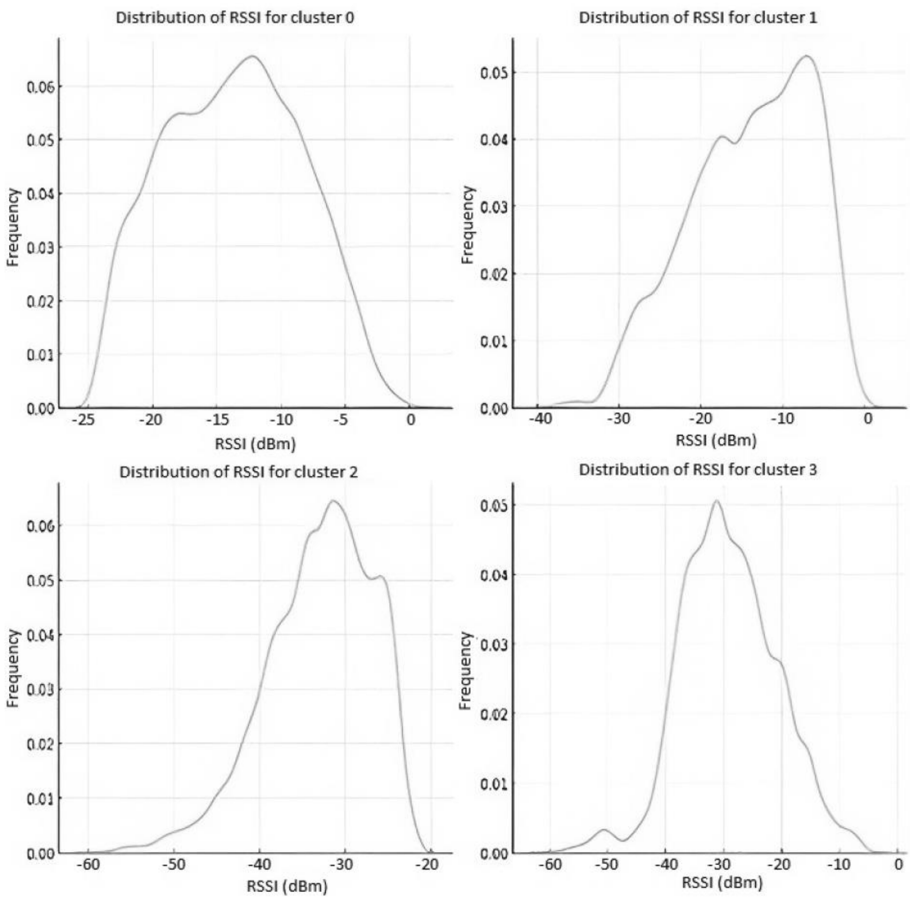

Fig. 7 – *RSSI distribution for each cluster.*

Network load and user density are dealt with using Kernel Density Estimation to determine the concentration of data points at each centroid. The locations of these routers are selected so as to maximize the bandwidth of high-density areas and provide increased performance and reliability during peak hours. This is particularly important in schools where the level of network traffic may fluctuate depending on the time of the day and depending on the season.

The environmental factors also play a crucial role in the proposed strategy. The influence of building materials on signal propagation is taken into account in the clustering algorithm; it takes into account the attenuation properties of different building elements: concrete walls, glass partitions, wooden doors, metal structures, and open spaces. These factors are essential for determining router placement strategies that can potentially address issues of signal loss and interference and thus enhance network performance in practical settings.

Through these extensive aspects, the suggested Wi-Fi deployment strategy not only live up to theoretical estimations but also addresses the technical needs of the building setting (see **Table 4**). This guarantees the network's ability to cope with abrupt changes in the environment and still effectively generate timely and high-quality Wi-Fi connectivity to supplement the general performance and productivity of the infrastructure deployment at hand.

Table 4

Suggested equipment's features.

Material	Attenuation Factor (dB)	Impact on Signal Strength
Concrete Walls	10-15	High
Glass Partitions	5-10	Moderate
Wooden Doors	3-5	Low
Metal Structures	15-20	Very High
Open Spaces	0-3	Negligible

A limitation of this study is the age of the measurement data, which precedes the adoption of modern Wi-Fi standards. Contemporary networks exhibit different propagation characteristics due to MIMO technology, higher channel bandwidths, and changes in device density. Therefore, the conclusions should not be generalized to current infrastructure without additional validation. The proposed workflow, however, is independent of the dataset and can be directly applied to newer measurements or simulation-based signal maps.

5 Conclusion

The aim of this study was to determine the optimal placement of Wi-Fi routers in a multi-floor educational building using the K-Means ML model. The findings offer a robust, evidence-based framework for enhancing signal quality, network reliability, and user satisfaction in complex environments. By leveraging ML. This study provides a scalable and adaptable solution that addresses the limitations of traditional methods. The proposed approach not only improves connectivity but also reduces dead zones and interference, ultimately enhancing the overall user experience. These insights can be applied to various multi-floor structures, paving the way for more intelligent and efficient network design in educational institutions and beyond.

Future research could expand on this work by integrating additional ML models and exploring real-time adjustments based on dynamic environmental changes. In addition, it is acknowledged that the proposed cluster-based router placement was derived analytically from the available dataset, without the possibility of performing new measurements at the recommended centroid positions. Because the dataset does not permit physical repositioning of access points, empirical validation through a new measurement campaign could not be carried out. Such validation is considered an important avenue for future work, as it would allow direct assessment of the signal coverage improvements expected from the optimized placement. Moreover, future work will integrate supervised ML models for predicting coverage quality and will implement several optimization algorithms (PSO, GA, SA) to identify placement configurations that maximize coverage and minimize signal degradation. Furthermore, the proposed router locations will be validated using simulation platforms such as ns-3 or ray-tracing tools to quantify improvements in coverage and throughput.

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