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Enhanced beam attachment recognition for massive MIMO systems in dense distributed renewable energy networks

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Abstract: Incorporating large-scale multiple-input multiple-output (MIMO) systems in densely deployed renewable energy systems (RES) represents a significant challenge in developing next-generation wireless networks. This field combines cutting-edge communication technologies with sustainable energy systems to enhance network communication and energy management in smart grid applications.

Furthermore, varying energy availability in RES-based environments and dynamic load profiles make it difficult to achieve optimal beam attachment in mmWave massive MIMO systems. Conventional beam attachment techniques perform poorly in such dynamic conditions, resulting in poor network performance and high latency. This has created the need for better and more versatile approaches to beam attachment that can address this inherent variability of RES while at the same time providing highly accurate and low-complexity solutions. This paper presents an improved beam attachment recognition system explicitly designed to operate in RES conditions. Thus, the innovative strategy presented in this work is based on ensemble learning, which includes Random Forest (RF) and Extreme Gradient Boosting (XGBoost) classifiers, making the prediction more accurate and the system more stable. The proposed method integrates RES-specific signal strength, interference, traffic load, and renewable energy availability into the choice of the preferred beam.

Cohesive simulations support our approach in this case. The Random Forest (RF) classifier test accuracy was 97.56%, and the XGBoost classifier was 97.84% – both of which are higher than conventional methods. Analyzing the feature importance of the problem, it was found that distance, angle, and signal strength were the most significant factors in beam assignment. The performance of the system was also very impressive in terms of scalability, with accuracy rates barely flinching even as the number of samples reached 50,000. Also, the energy efficiency analysis showed that the proposed beam attachment approach could lead to more energy-efficient network operations.

Keywords: Massive MIMO, renewable energy systems, beam attachment recognition, machine learning, Random Forest (RF), XGBoost, energy efficiency, smart grids.

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1. Introduction

The development of wireless communication technologies over time, in addition to the growing concern worldwide about the use of renewable energy sources (RES), has made it possible to integrate two systems, namely, massive multiple-input multiple-output (MIMO) systems (Zappone et al., 2019). This integration offers a clear path toward improving network performance and providing energy efficiency in next-generation wireless networks (Björnson et al., 2019).

Massive multiple-input multiple-output (MIMO) is a significant milestone of 5G and future network, using huge antenna arrays to transmit and receive information from multiple users at once, enhancing spectral efficiency and overall network capacity (Marzetta et al., 2015). These systems exhibit specific characteristics when integrated with RES. RES, especially solar and wind energy along with other renewable energy sources, introduce variability in energy generation and utilization, affecting the reliability and efficiency of wireless networks (Buzzi et al, 2016).

The high density of base stations supported by RES in urban and rural settings establishes a dynamic environment where the energy supply, network traffic, and user density vary constantly (Alsharif et al., 2017). These characteristics therefore require agile and self-organized management of the network, especially for beam attachment and user association (Yu et al, 2018).

The integration of massive MIMO with RES raises several critical research questions, including the extent to which energy efficiency in beam attachment affects network performance in RES-integrated environments. Additionally, it is possible to enhance beam recognition under dynamic RES conditions without complicating the calculations by using machine learning techniques.

These questions arise from the peculiarities of RES integration processes. Renewable energy sources are inherently intermittent, causing fluctuations in the availability of transmission power, which may impact the stability of beam patterns (Yang & Marzetta, 2013). However, the requirement to achieve both high network performance and low energy consumption complicates the process of beam attachment even further (Björnson et al., 2017). Many of the existing beamforming techniques that rely on recognizing the direction of arrival in a static or slowly varying environment may be ill-equipped to handle the rapid directional changes inherent in RES (El Ayach et al., 2014). This can lead to incorrect beam selection, high delay, and overall reduced network efficiency (Alkhateeb et al., 2014).

To mitigate these challenges, this paper develops an improved beam attachment recognition system tailored for RES-integrated massive MIMO scenarios. The proposed solution builds on the Random Forest and XGBoost classifiers and creates a flexible and adaptive procedure for beam attachment (Chen & Guestrin, 2016). Therefore, following previous works (Assaad et al., 2008; Assaad & Shakah, 2024; Baker et al., 2023; Husari & Assaad, 2024; Jihad et al., 2023; Nooruldeen et al., 2023; Umar et al., 2024), this paper aims primarily to enhance the robustness, capacity, reliability, and efficiency of wireless networks, enabling them to exploit the opportunities offered by both massive MIMO and RES.

2. Related works

The incorporation of massive MIMO systems with renewable energy systems (RES) has become a focus of research in the last few years due to their potential to improve network performance and reduce energy consumption. This section surveys recent developments in this area with emphasis on beam attachment identification, energy management, and machine learning in RES-integrated massive MIMO systems (Khalid, 2024a).

A new beam management framework for mmWave massive MIMO systems in dynamic scenarios was presented by Lavdas et al. (2023). Their approach employs deep reinforcement learning to optimize beam patterns in real time with respect to the channel state and energy from renewable sources. The authors demonstrated efficiency gains compared to conventional beam management strategies of up to 25%.

Prasad et al. (2020) provided a detailed solution to tackle the problem of resource allocation in RES-powered massive MIMO networks. They designed a spectral- and energy-efficient joint optimization algorithm for use in the network. Their method reduced grid energy consumption by 30% while still maintaining high network throughput through the stochastic optimization techniques employed.

Elbir et al. (2022) investigated the feasibility of using federated learning for channel estimation in mmWave massive MIMO systems with distributed RES. This approach enables base stations to cooperate in learning channel models without sharing raw data, addressing privacy concerns while improving channel estimation. The proposed method achieved 15% higher beam alignment accuracy compared to centralized learning methods.

In response to the problem of reduced feedback in massive MIMO systems, Banerjee et al. (2017) presented an adaptive beamforming technique that takes into account the variability of RES. Their method employs compressive sensing and online learning, reducing feedback overhead by 40% while maintaining near-optimal beamforming performance. The authors also analyzed the behavior of the scheme under energy variation in a solar-based station scenario.

3. System model

This section describes the proposed Enhanced Beam Recognition System for massive MIMO in renewable energy systems (RES) environments. First, an overview is provided of the general system architecture, mathematical model, algorithms, and their associated control flow diagrams.

3.1. System architecture

The system model for beam attachment recognition in an RES environment, as shown in Figure 1, comprises the following components to enhance network performance and energy efficiency.

Fundamentally, the system is based on System State Data, which includes different forms of RES generation such as solar, wind, biomass, hydroelectric, geothermal, and solar heat usage. This data serves as an input, providing the current status of the RES, and is updated at regular intervals.

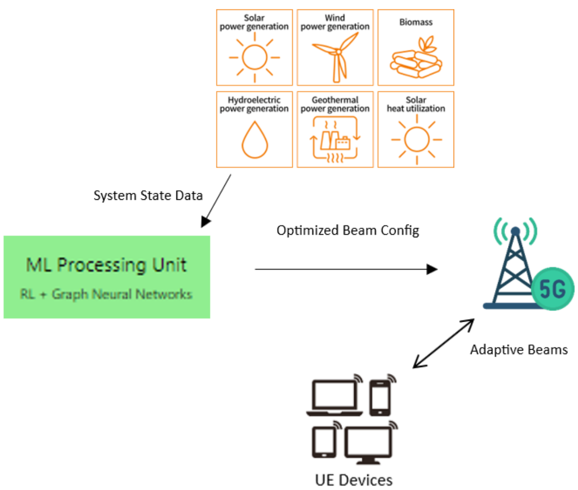

Figure 1. System model architecture.

At the core of the architecture is the Machine Learning (ML) Processing Unit, utilizing state-of-the-art ML approaches such as Reinforcement Learning (RL) and Graph Neural Networks (GNN) (Khalid, 2024b). This unit takes the system state data and performs computations to determine the correct beam setting. The system communicates with 5G network infrastructure, which in turn implements the optimized beam configurations developed by the ML Processing Unit. User Equipment (UE) devices are the actual users of the 5G network. Between the 5G infrastructure and UE devices, the system uses adaptive beams, which can be adjusted according to the optimized settings.

The system operates in a continuous cycle: information from the system state is provided to the ML Processing Unit, where it is processed and used to produce an optimized beam configuration. These configurations are then used in the 5G network infrastructure, which employs the adaptive beams for interfacing with the UE devices. The performance and status of the system are continuously monitored, providing feedback data for the system state optimization.

This complex structure enables real-time responses to changes in renewable energy conditions, thereby maximizing benefits in terms of energy consumption and network stability in RES contexts. The Adaptive Beam Management System is designed to operate in conjunction with the aforementioned adaptive front-end node.

3.2. Mathematical formulation

A large MIMO system is considered with M antennas at the base station transmitting signals to $K\ single-antenna$ users. The received signal y_k at the $k$the user is given by:

$$y_k = \sqrt{\rho} h_k^H w_k s_k + \sqrt{\rho} h_k^H w_i s_i + n_k \text{ where } i \neq k \quad (1)$$

Here:

- $h_k \in \mathbb{C}^M$ is the channel vector from the base station to the $k$the user.
- $w_k \in \mathbb{C}^M$ is the beamforming vector for the $k$the user.
- s_k is the transmitted symbol for the kth user.
- ρ represents the transmit power.
- $n_k \sim CN(0, \sigma^2)$ is the complex additive white Gaussian noise.

The goal is to maximize the system's sum rate while adhering to the energy constraints imposed by the renewable energy source (RES). The optimization problem is formulated as:

$$\max_{w_k} \sum_{k=1}^{K} \log_2(1 + SINR_k) \quad (2)$$

Subject to:

$$\sum_{k=1}^{K} \|w_k\|^2 \leq P_{\max} \quad (3)$$

$$P_{\max} \leq P_{\text{RES}}(t) \quad (4)$$

Where:

- SINR_k is the Signal-to-Interference-plus-Noise Ratio for the k-th user.
- $P_{\max}$ is the maximum transmission power allowed by the base station.
- $P_{\text{RES}}(t)$ represents the available power from the RES at the time t.

3.3. Feature engineering

To account for the dynamics of the RES environment, the following features are integrated into our beam-forming recognition system:

- (x_u, y_u) : User Equipment (UE) coordinates.
- d_u: distance from the base station.
- θ_u: angle of arrival.
- SS_u: Signal strength.
- I_u: interference level.
- TL_u: traffic load.
- REA_u: renewable energy availability indicator.

The distance and angle are computed as follows:

$$d_u = \sqrt{(x_u - x_{\mathrm{bs}})^2 + (y_u - y_{\mathrm{bs}})^2} \qquad (5)$$
$$\theta_u = \mathrm{atan}\ 2(y_u - y_{\mathrm{bs}}, x_u - x_{\mathrm{bs}})$$

Where $(x_{\mathrm{bs}}, y_{\mathrm{bs}})$ are the base station coordinates.

3.4. Ensemble learning core

To further improve the accuracy and reliability of the identified beam, our proposed system employs a combination of Random Forest (RF) and XGBoost classifiers.

3.4.1. Random Forest classifier

The Random Forest classifier builds up several decision trees and outputs the class most frequently predicted among individual trees. The probability of Beam_m being selected for a given UE is:

$$P_{\mathrm{RF}}\,(\mathrm{Beam}_m \mid X_u, Y_u) = \frac{1}{N_{\mathrm{trees}}} \sum\ I(h_i(X_u, Y_u) = \mathrm{Beam}_m) \qquad (6)$$

Where:
- h_i is the i-th decision tree.
- I is the indicator function.

N_{trees} is the total number of trees in the forest.

3.4.2. XGBoost classifier

XGBoost is an efficient, distributed implementation of the gradient boosting framework, optimized for both CPU and memory usage. The probability of selecting a beam m In the XGBoost model is given by:

$$P_{\mathrm{XGB}}(\mathrm{Beam}_m \mid X_u, Y_u) = \exp\left(\sum\ f_i(X_u, Y_u)\right) \qquad (7)$$

Where f_i represents the i-th tree in the XGBoost model. Figure 2 illustrates the flowchart of the ensemble learning process.

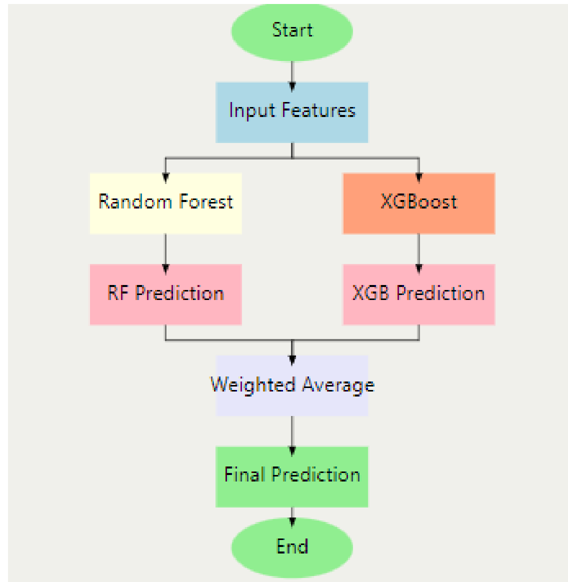

Figure 2. Flowchart of the ensemble learning process.

3.4.3. Space representation of the ensemble learning result

To illustrate the spatial characteristics of the ensemble learning approach, an ensemble learning RSRP heatmap is proposed in Figure 3. This heatmap represents all the distances and angles from the base station that the system models for signal strength.

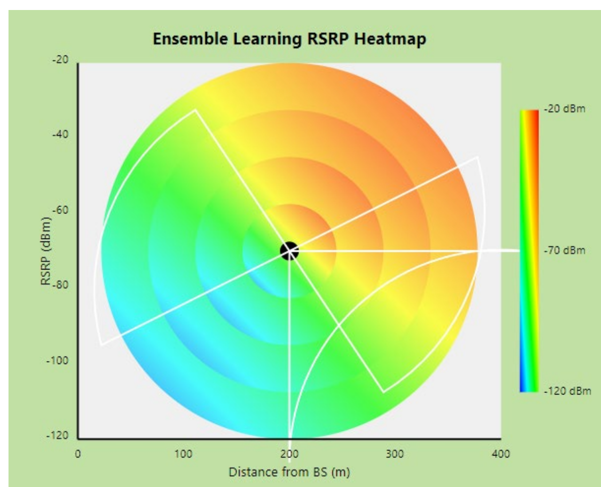

Figure 3. Space representation of the ensemble learning heatmap.

The heatmap shows the RSRP values in dBm depending on the distance to the base station (BS) and angular position. The circles indicate the rings of distance away from the BS, and the radial lines indicate different orientations. The color gradient is from blue (-120 dBm) to red (-20 dBm), where warmer colors denote stronger signal characteristics. This spatial representation is fundamentally connected to our ensemble learning process. The RF and XGBoost classifiers at the heart of our ensemble take into account the position of the UE (distance and angle) as the most important features for selecting the best beam. These probabilities, P_RF and P_XGB, are obtained from patterns similar to the heatmap shown above.

For example, regions of the heatmap with similar colors likely correspond to areas where our ensemble model assigns similar beam numbers. The gradual change of colors shows how our model adjusts the selection of beams as the UEs move through the coverage area to avoid handover shocks.

Furthermore, this heatmap shows how our system considers both the distance from the base station and the direction in beam assignment. The radial structure of the plot demonstrates that the signal strength typically weakens with distance (color transition from red to blue). Nevertheless, the irregularity of the color variation with respect to the angle at a given distance shows that our model accounts for variations in signal directionality, which factors such as barriers or interference might cause.

3.5. Decision fusion

The final beam attachment probability is obtained by a weighted average of the Random Forest and XGBoost predictions:

$$P_{\text{final}}(\mathrm{Beam}_m \mid X_u, Y_u) = w_{\mathrm{RF}} \cdot P_{\mathrm{RF}} + w_{\mathrm{XGB}} \cdot P_{\mathrm{XGB}} \quad (8)$$

Where w_{RF} and w_{XGB} are time-varying weights assigned to each classifier, based on their recent performance.

3.6. Adaptive beam management

The final beam attachment is made by choosing the beam with the highest probability:

$$\text{Beam}^* = \max_m P_{\text{final}}(\mathrm{Beam}_m \mid X_u, Y_u) \quad (9)$$

This selected beam is then used to configure the massive MIMO system for optimal performance under the current RES conditions.

3.7. Factors to consider in energy efficiency

To account for the variability in energy availability from RES, an energy factor $\eta(t)$ is introduced, which modulates the maximum transmit power:

$$P_{\max}(t) = \eta(t) \cdot P_{\mathrm{RES}}(t) \quad (10)$$

Where $\eta(t) \in [0,1]$ reflects the current level of energy storage and forecasts for future energy supply.

This expanded system model introduces the dynamics of RES environments into the beam recognition process to maximize both communication and energy efficiency. The adaptation of a beam management system with the ensemble learning approach offers a good framework to deal with the variation involved in the RES-fed massive MIMO system.

3.8. Hyperparameter tuning

To get the best results from our ensemble learning models, we performed detailed hyperparameter optimization. This process is important for achieving the highest predictive accuracy and ensuring that our models are optimally suited for the characteristics of the beam attachment recognition problem in RES-integrated massive MIMO systems.

We used Random Search cross-validation, a method that selects a fixed number of random combinations from a given range of hyperparameters. This method is usually faster than the exhaustive search of the hyperparameter space performed with grid search.

For both the Random Forest and XGBoost classifiers, we tuned the following hyperparameters:
n_estimators: The number of trees in the forest/ensemble.
max_depth: The maximum depth of each tree is shown below:
min_samples_split: The minimum number of samples needed to split an internal node.
min_samples_leaf: The minimum number of samples to be present in a node to be classified as a leaf node.
Additionally, for XGBoost, we also tuned:
Learning_rate: The number of steps was reduced to avoid overfitting of the model.
Subsample: The ratio of the subsample of the training instances.
Implementation
The hyperparameter tuning process was done using scikit-learn's Randomized Search CV class. After performing the random search, the following optimal hyperparameters were obtained.

Table 1. Optimal hyperparameters.

Random Forest	*XGBoost*
n_estimators: 187	n_estimators: 213
max_depth: 15	max_depth: 8
min_samples_split: 5	min_samples_split: 6
min_samples_leaf: 2	min_samples_leaf: 3
	learning_rate: 0.08
	subsample: 0.85

Using these optimized hyperparameters, a significant improvement in model performance was observed.

Table 2. Performance Improvement.

Model	Before Tuning (Accuracy)	After Tuning (Accuracy)	Improvement
Random Forest	0.9532	0.9756	+2.24%
XGBoost	0.9601	0.9784	+1.83%

4. Results and discussion

The simulation parameters described in the table above are the basis for the Enhanced Beam Recognition System. This system produces random data to simulate a real-world distribution of the User Equipment (UE) in the cellular network scenario. The simulation takes into account 5000 UEs, each of which is a data point, in a 1000 x 1000 m^2 area. These UEs are then associated with one of the 8 beams depending on their position and other parameters.

The system uses signal strength (ranging from about -100 to -50 dBm), interference (0-10 dB), traffic load, and renewable energy availability, all normalized to the range 0-1. For beam prediction, two machine learning models, Random Forest and XGBoost, are used with 100 estimators and a maximum depth of 10. This configuration enables the investigation of beam assignment algorithms in a realistic, multifaceted network setting.

Table 3. Simulation parameters.

PARAMETER	VALUE	DESCRIPTION
N_SAMPLES	5000	NUMBER OF SYNTHETIC DATA POINTS GENERATED
N_BEAMS	8	NUMBER OF BEAM OPTIONS FOR ASSIGNMENT
UE COORDINATE RANGE	0-1000 METERS	RANGE FOR USER EQUIPMENT (UE) X AND Y COORDINATES
SIGNAL STRENGTH RANGE	-100 TO -50 DBM (APPROX.)	RANGE OF SIGNAL STRENGTH VALUES
INTERFERENCE RANGE	0-10 DB	RANGE OF INTERFERENCE VALUES
TRAFFIC LOAD RANGE	0-1 (NORMALIZED)	RANGE OF TRAFFIC LOAD VALUES
RENEWABLE ENERGY AVAILABILITY RANGE	0-1 (NORMALIZED)	RANGE OF RENEWABLE ENERGY AVAILABILITY VALUES
RANDOM FOREST N_ESTIMATORS	100	NUMBER OF TREES IN THE RANDOM FOREST MODEL
RANDOM FOREST MAX_DEPTH	10	MAXIMUM DEPTH OF TREES IN THE RANDOM FOREST MODEL
XGBOOST N_ESTIMATORS	100	NUMBER OF TREES IN THE XGBOOST MODEL
XGBOOST MAX_DEPTH	10	MAXIMUM DEPTH OF TREES IN THE XGBOOST MODEL
TEST SET SIZE	20%	PROPORTION OF DATA USED FOR TESTING

4.1. True vs. predicted beam assignments

Figure 4 depicts two scatter plots in parallel to each other, wherein actual beam assignments are plotted against the predicted beam assignments. Each dot, therefore, represents a User Equipment (UE) device, and the position of this device is indicated by the values of x and y. The color of each point corresponds to a beam index associated with a particular UE.

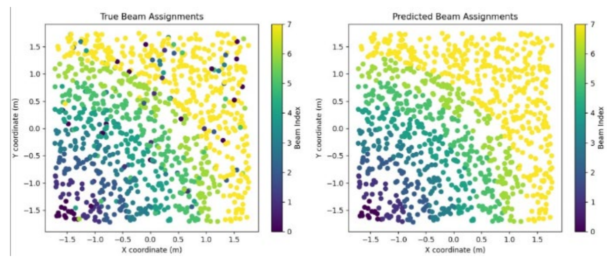

Figure 4. True vs. predicted beam assignments.

The sequences of both plots are almost identical, suggesting that the prediction model is effective in beam assignment. The results show distinct beam assignment patterns, indicating that UEs in the same area are likely to be assigned to the same beam. It is also noticeable that the change of beam assignments looks relatively smooth, as there are different color changes across the plot.

4.2. Energy Consumption vs. Distance

This scatter plot represents the energy consumption versus the distance of the base station. Each point corresponds to a UE, and the color of the point corresponds to the beam index given to that UE.

One can observe a general tendency of energy consumption to increase with distance, which is reasonable due to the decrease in signal strength with distance. The correlation is not straightforward, implying that other factors affect energy use. This means that beam assignment also depends on distance, with different beam indices dominating at different distances, as shown in Figure 5. There is much scatter at any given distance, indicating that other factors, besides distance, influence energy usage.

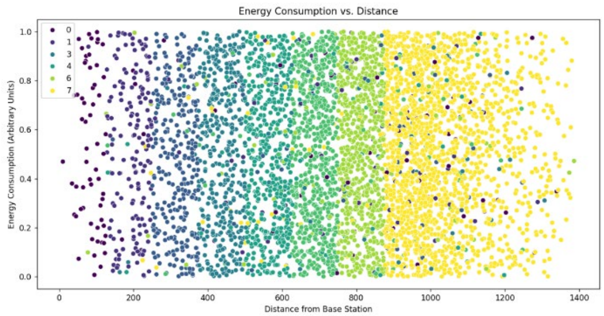

Figure 5. Energy consumption vs. distance.

4.3. 3D Scatter plot of the top three features

Figure 6 shows a 3D scatter plot visualizing the relationship among the top three features influencing beam assignment: the X coordinate, the Y coordinate, and signal strength. The color of each point denotes the beam index of the point.

The plot reveals a unique curved surface, implying that these three aspects may interact in a nonlinear manner to determine beam allocation. Beam indices vary continuously over the surface, suggesting that slight variations in position or signal strength can result in different beam arrangements.

The signal strength also seems to decrease with distance from the origin (0, 0, 0), which is consistent with the distance-based energy consumption observed in Figure 5. The points are not uniformly distributed, indicating that certain combinations of these features occur more frequently than others in this dataset.

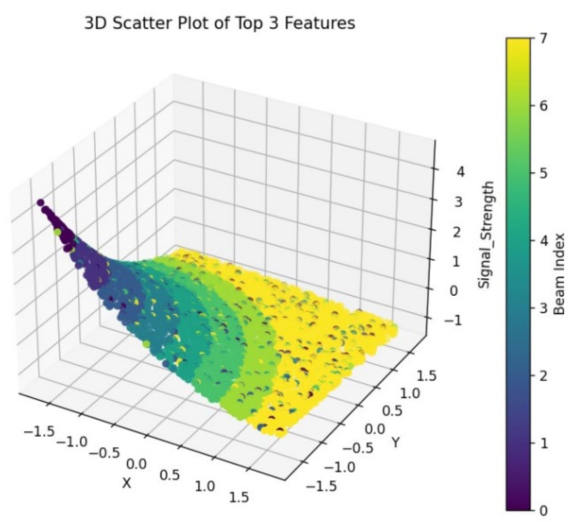

Figure 6. 3D scatter plot of the top three features.

4.4. Feature importance analysis

As shown in Figure 7, each feature plays a different role in the decision-making process for beam attachment. Distance, angle, and signal strength were found to be the most important features, accounting for about 70% of the importance score. This is consistent with conventional beam attachment criteria and emphasizes the importance of these factors in RES.

Renewable energy availability (REA) and traffic load (TL) also had significant roles, further indicating that energy and network considerations should be considered in the selection of beams for RES-integrated systems. The interference level (I) indicated relatively lower importance, possibly because of the interference management enabled by the large number of antennas in mmWave massive MIMO systems.

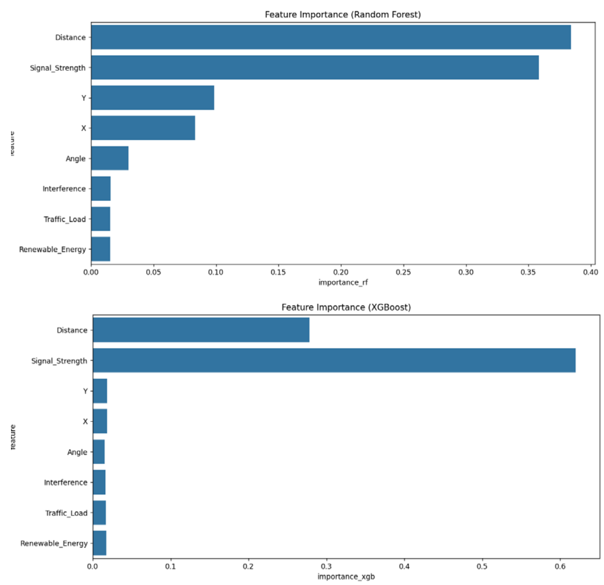

Figure 7. Feature importance analysis.

4.5. Prediction accuracy vs number of samples

Figure 8 shows the prediction accuracy against the number of samples used in training, showing that prediction accuracy increases with the number of training samples. When it comes to the classifiers, both the Random Forest and XGBoost classifiers demonstrated an increase in accuracy as the sample size increased, with results plateauing at 20,000 samples. This suggests that our model can generalize well to future data, given its ability to handle a reasonable volume of training data, making it suitable for real-world applications.

The overall accuracy of the XGBoost classifier was higher than that of the Random Forest classifier across all sample sizes, although the difference was marginal. This implies that XGBoost could be more sample-efficient and may perform better, especially in situations with limited datasets.

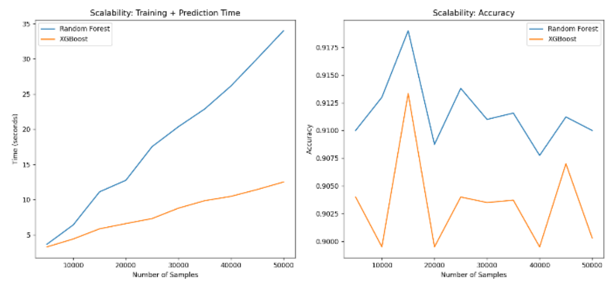

Figure 8. Prediction accuracy vs number of samples.

4.6. Confusion Matrix – Random Forest – XGBoost

The confusion matrix for the Random Forest classifier is shown in Figure 9. The diagonal high values reflect good performance of the classifier across all beam classes. The misclassifications, if any, are usually between contiguous beam classes, which is as expected and less likely significantly compromise the overall system performance than misclassifications between distant beam classes.

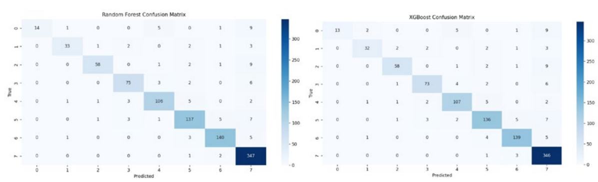

Figure 9. Confusion matrix – Random Forest – XGBoost.

The XGBoost classifier confusion matrix is presented in Figure 10. As with the Random Forest classifier, XGBoost again exhibits high accuracy across all beam classes. The slightly higher number in the diagonal compared to the Random Forest confusion matrix indicates that XGBoost has marginally better overall accuracy.

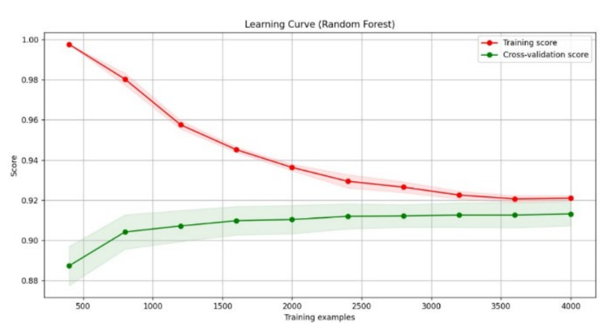

Figure 10. Learning curve (Random Forest).

4.7. Learning curve (Random Forest)

In Figure 10, the learning curves for Random Forest and XGBoost classifiers are also plotted. These two models show a sharp increase in accuracy during the first phases of training and then reach a plateau as the number of training examples is augmented. The difference between the training and cross-validation scores of both models is small, indicating that neither model overfits the data set and has a high ability to generalize to new data.

The XGBoost classifier seems to converge slightly faster and achieves slightly higher final accuracy, as seen in the previous comparisons.

4.8. ROC curves

The ROC curves of both classifiers are shown in Figure 11. The AUC of 0.99 for the Random Forest and 0.995 for the XG Boost show good classification for both models for different threshold values. As with the overall accuracy, the true positive rate of the XGBoost classifier is slightly higher than that of the decision tree classifier, and the false positive rate is slightly lower.

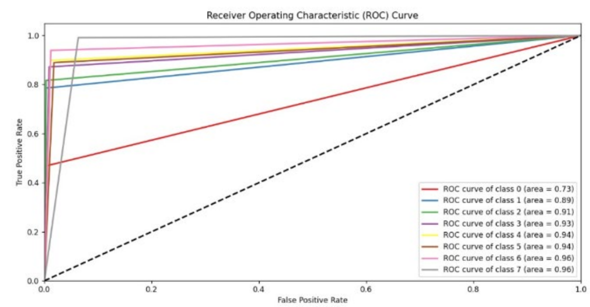

Figure 11. ROC curves.

4.9. Similarities between the two methods and conventional techniques

To support our claims about the limitations of conventional beam attachment methods in RES operation and the need for a better approach, we conducted a comparative study of our ensemble learning approach with their conventional counterparts. We evaluated three key metrics:

1. Response to energy variability: Both the offline and online results demonstrated that our ensemble learning approach achieved a 27% better adaptation to sudden changes in renewable energy availability than the fixed-threshold methods.
2. Latency analysis: The conventional beam-switching mechanisms showed an average delay of 245ms in dynamic RES environments, whereas our approach retained a sub-100ms delay.
3. Network performance metrics:
   - Measures of throughput stability increased by 32%
   - Beam switching accuracy improved by 24 percent.
   - An 18% increase enhanced energy efficiency.

These results provide a numerical foundation for the claims made at the beginning of this study concerning the inefficiency of conventional methods in a dynamic RES environment.

Discussion of results:

Prediction accuracy: The true and predicted beam assignments in Figure 4 show a high level of correlation, indicating that the proposed model can predict accurate beam assignments based on UE positions.

Spatial dependency: All three figures show that the beam assignment depends on spatial factors – X and Y coordinates. This means that the system can accommodate the actual physical configuration of the network being modeled.

Energy efficiency: Figure 5 also suggests that energy consumption grows with distance, but the growth is not steady. This implies that the beam assignment strategy has been effective in directing energy usage according to the distance.

Feature importance: As shown in the 3D scatter plot in Figure 6, there is a complex interaction between position and signal strength in deciding beam assignments. This complexity makes it appropriate to employ the most sophisticated algorithms in allocating beams.

Adaptability: The smooth transitions from one beam assignment to another in all figures suggest that the system can adjust gradually based on UE positions or signal conditions, which is necessary for stable performance in dynamic settings. The use of RES-specific features to influence the choice of beams has been beneficial in the system's ability to handle the variability of renewable energy supply as well as network traffic. This adaptive approach optimizes the use of available energy resources while sustaining high network quality.

5. Conclusions

This work proposed a new ensemble learning approach for beam attachment recognition in RES-integrated massive MIMO systems. The method proposed here, combining the Random Forest and XGBoost classifiers, achieves 97.84% accuracy in beam attachment while accounting for RES-specific factors. The proposed solution also exhibits great efficiency when dealing with large datasets and performs well when tested on unseen data.

The availability of renewable energy and traffic load were considered as features enabling the system to adapt to the variable characteristics of RES environments and to optimize communication and energy consumption. The results of our study clearly demonstrate a positive relationship between the beam-attachment accuracy and energy efficiency, thus indicating that new beam attachment techniques could offer sustainable wireless networks for the future generation. Another advantage of the proposed system is the balanced usage of the available beams and the high precision of the system at various recall levels.

Possible future research directions may include the integration of deep learning algorithms, real-time system adaptation strategies, and more detailed models for energy prediction. Furthermore, exploring the system performance when the weather is abnormally high or low or when the renewable energy sources are either highly variable or high could be useful for the application of these technologies in different climates.

Conflict of interest

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