OPEN ACCESS

Saudi Journal of Engineering and Technology
Abbreviated Key Title: Saudi J Eng Technol
ISSN 2415-6272 (Print) |ISSN 2415-6264 (Online)
Scholars Middle East Publishers, Dubai, United Arab Emirates
Journal homepage: https://saudijournals.com

Original Research Article

Optimizing Path Loss Prediction for Air-Ground Communication Systems Using Hybrid Machine Learning Models: A Case Study of Linear Regression and PSO-Optimized Gradient Boosting Regressor

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DOI: https://doi.org/10.36348/sjet.2025.v10i06.005 | **Received:** 09.05.2025 | **Accepted:** 14.06.2025 | **Published:** 19.06.2025

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Abstract

This paper examines how linear regression in machine learning enables the prediction of air-ground path loss through environmental parameters such as temperature, humidity, and atmospheric pressure measurements. The paper demonstrates that temperature plays the most significant role in determining path loss, while humidity and atmospheric pressure contribute at a lower level. A high level of accuracy defines the linear regression model, which demonstrated efficient path loss prediction through a Mean Absolute Error (MAE) of 0.2995. The model demonstrates effective capabilities for system improvements during changing atmospheric conditions because the trend line shows the smooth progression of predicted and actual values. A hybrid model produced enhanced prediction accuracy when particle swarm optimization and gradient-boosting regressor parameters were optimized to establish the new model system. The optimized model substantially declined MAE to 0.0435, which verified its improved predictive capacity regarding absolute path loss values. A performance-maximized model resulted from tuning relevant parameters to set n_estimators equal to 56, learning rate to 0.1, and max_depth to 9. The optimized model accurately predicts path loss in communication networks, preparing it for on-site deployment. This research serves as a basis for further investigation, integrating other environmental elements, including wind speed, rainfall and elevation levels, and testing alternative state-of-the-art machine learning methods. Future improvements in these procedures can boost the flexibility and reliability of networks with an emphasis on air-ground systems. Research findings indicate that PSO-GBR hybrid models possess a high potential for path loss prediction, creating new possibilities for future air-ground communication systems and emerging technologies such as low-altitude satellites, air taxis, and unmanned aerial vehicles (UAVs).

Keywords: Path Loss Prediction; Hybrid Machine Learning Models; Air-Ground Communication; Particle Swarm Optimization (PSO); Gradient Boosting Regressor (GBR).

1. INTRODUCTION

VHF air-to-ground communications remain an integral part of flight today, their lifeline connections for voice and data transmission between air and ground transport, bringing life to the world of flight (Ozemen *et al*., 2024). With aerial missions more and more tending to grow in complexity, from manned combat and civil aviation to UAS, greater demands are being placed on more hardened, more reliable, and more advanced communications infrastructure that can function reasonably well under a broad spectrum of atmospheric and environmental conditions. However, the common prevalence of multipath propagation effects at a higher frequency—most notably in dynamic atmospheric conditions—rules out excessive restriction on conventional modelling paradigms. This involves developing innovative solutions to understand air-ground communication channels' dynamic and elusive nature.

In this context, Artificial Intelligence (AI) and Machine Learning (ML) modelling of the propagation in VHF channels provides a new revolutionary alternative (Mahmood *et al*., 2022). Their predictability, flexibility, and data-centricity can challenge conventional models to newer heights and facilitate environment and channel learning in real time to emulate steady and enhanced multipath effects. This article presents AI/ML synergy and adaptive multipath air-ground channel model modelling under any atmospheric condition for VHF channels.

General propagation models used to simulate the VHF propagation, i.e., Free Space Path Loss, Two-Ray Ground Reflection model, and empirical models like Hata and Okumura-Hata models lack the inherent weakness of not possessing the capability of sensing dynamic changes in the environment (Anusha *et al*., 2017). They rely on static assumptions about the environment and mean-case values of environmental parameters and lack environmental context awareness. They thus cannot operate in dynamic air-ground communication systems rich in multipath (Matolak, 2012).

Khawaja *et al*. (2019) presented an exhaustive overview of air-to-ground (A2G) channel models, particularly underlining that UAVs and other flying vehicles are considerably susceptible to variations in propagation conditions with speed, elevation, and ground. The investigation required models capable of delivering a height-varying variation of line-of-sight blockage, loss in the path, and fast-time-varying Doppler impacts to a greater extent. The same drone or UAV channel modelling was also achieved by Moraitis *et al*. (2023), presenting successful system-level simulations as pivotal in enabling temporal and spatial channel dynamics not enabled by traditional models.

With more dynamic air platforms and more turbulent atmospheric conditions due to global climate change, simulating the behaviour of VHF signals is a task that becomes progressively more difficult. Multipath propagation by signal reflection off terrain, buildings, and atmospheric layers can lead to fading, delay spread, phase distortion, and signal cancellation. Extremely sensitive to time-varying and environmental parameters such as humidity, temperature gradients, wind, and pressure gradients.

Recent research has established the possibility that fixed models cannot account for variability contained in such dynamic effects. To overcome the above-said limitation, researchers are opting for machine learning approaches with the capability of adaptability, online learning, and prediction. Machine Learning (ML) and Artificial Intelligence (AI) can enable future wireless communication systems for data-driven and real-time intelligent decision-making. Bhattacharyya *et al*. (2023) authored an extensive work on ML and deep learning in satellite communications. They stated that they can learn the non-linear mapping of the signal quality and channel parameters. The approaches have proven to enhance reliability in links, prediction of channel state transitions, and signal processing optimization across satellite networks. The air-ground propagation and satellite analogy—both under harsh environmental conditions—naturally and hopefully make it a good idea to utilize AI/ML methods on VHF air-ground channels.

Specifically, Random Forest, Gradient Boosting, and Support Vector Regression (SVR) machine learning algorithms and deep learning models such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) have been found to be more accurate in identifying wireless channel spatiotemporal patterns. Models can be learned from existing data, updated incrementally over time continuously with new data, and predict such vital channel statistics as path loss, signal-to-noise ratio (SNR), and delay spread with high accuracy.

The same is followed by research work by Khalid *et al*. (2024). They validated ML-based hybrid Free Space Optics (FSO)/RF systems against fog and smog and demonstrated the performance of intelligent algorithms to simulate and tackle atmospheric attenuation. Their operations under adverse weather conditions demonstrate the possibilities of AI/ML in simulating multipath effects under temporally changing atmospheric conditions in the VHF frequency band.

Atmospheric conditions have been found to have a determinative role in transmitting VHF signals. Temperature, relative humidity, wind speed, and barometric pressure are among the most rudimentary parameters likely to alter the atmosphere's refractive index and thereby cause refraction, ducting, and scattering. These also influence signal strength, delay profiles, and Doppler shifts—problems of the most rudimentary nature to VHF-based systems.

Liu *et al*. (2024) described the dynamic nature of near-space communication systems in transitional atmospheric regions with humongous propagation variation. They wanted to understand how cognitive, adaptive systems would learn from the atmosphere and adjust communication parameters accordingly. The synergy between ML and meteorological data sources—weather stations and satellites—can be leveraged to provide dynamic, environment-adaptive VHF channel propagation modelling. Likewise, Sabuj *et al*. (2023) also introduced the idea of low-altitude satellite constellations for air-ground communication. The platforms interact closely with lower layers of the atmosphere, where turbulence and heterogeneity are formidable attributes. Authors suggested the need for models that were robust enough to be in a position to acclimatize to the environment and put forward AI-based approaches that could incorporate real-time environmental inputs.

The AI/ML multipath propagation adaptive modelling is distinct from all the other remaining hard rule-based techniques. Here, the propagation models are trained from enormous signal measurement databases, aircraft telemetry, terrain, and meteorology. They learn later on in real-time and real-time propagation parameters such as path loss and multipath delay. This kind of system utilizes ML algorithms to pattern recognition the way atmospheric conditions affect signal propagation. Recurrent models like LSTM networks can even learn earlier signal states and leverage temporal correlations when predicting future states. It is beneficial when flying aircraft through regions containing several climatic zones in which real-time revision of propagation estimates will be crucial for communication reliability.

The result is an even more robust air-ground communication link that peers forward and compensates for multipath conditions and auto-tunes based on operating environment feedback. While there has been some attempt to rationalize the promise of AI/ML in wireless systems, no such effort, to the authors' knowledge, has specifically confronted the unique challenges of VHF air-ground systems plagued by dynamically varying atmospheric conditions. The uniqueness of the VHF band—insensitivity to certain forms of attenuation but sensitivity to diffraction and multipath based on terrain and long distances—requires special research.

Aside from that, existing propagation models do not consider using meteorological data and real-time interaction. What is needed is high-impact research to create end-to-end systems combining environmental monitoring, machine learning, and signal measurement to provide continuous and adaptive propagation models. It should be ensured that it is worthwhile to fill this gap. Apart from building air traffic control networks and aircraft communication networks, these models can also give rise to the potential to make future networks of low-altitude satellite systems, drones, and air taxis realizable.

2. METHODOLOGY

This study utilizes machine learning algorithms, namely linear regression, a hybrid Particle Swarm Optimization (PSO) and Gradient Boosting Regression (GBR), to predict path loss in air-ground communication systems. Temperature, humidity, and atmospheric pressure are input parameters for predicting the path loss as the response variable.

(i) Data Collection and Preprocessing

Realistic measurements for the environment, i.e., temperature (in Celsius), humidity (in percentage), and atmospheric pressure (in hectopascals), along with respective path loss values (in decibels, dB), were derived. The data utilized in this work is presented in Table 1 below. This data is converted into a Pandas Data Frame to ease manipulation and analysis. The features—temperature, humidity, and atmospheric pressure—are selected as the independent variables (X), and path loss is the dependent variable (y). The data are split into training and test sets using sklearn. model_selection's train_test_split function and 80% of the data are utilised for training and 20% for testing.

Table 1: The Data used for the Study

Temperature (°C)	Humidity (%)	Pressure (hPa)	Path Loss (dB)
25	60	1015	120
28	65	1013	125
30	70	1012	130
22	80	1016	115
18	50	1017	110
15	55	1014	105
28	60	1013	125
26	58	1012	118
29	66	1015	127
21	72	1014	112

(ii) Linear Regression Model

The first model employed is a simple linear regression. This model attempts to find the relationship between the independent variables and the dependent variable, path loss, based on the following equation:

$$Path\ Loss = \beta_0 + \beta_1 * Temperature + \beta_2 * Humidity + \beta_3 * Pressure \quad (1)$$

where,

β_0 is the intercept,

β_1, β_2 and β_3 are the coefficients for temperature, humidity, and pressure, respectively?

The model is trained using the Linear Regression class from sklearn. linear_model, and predictions are made for the test set. The Mean Absolute Error (MAE) is calculated to evaluate the model's performance:

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

where:

$\hat{y}_i$ is the predicted path loss,

y_i is the actual path loss,

n is the number of test samples.

(iii) Hybrid PSO-GBR Model

For improved prediction accuracy, the study uses a PSO and GBR hybrid model. PSO is used for hyperparameter tuning of the GBR model. The GBR model, being an ensemble learning algorithm, is tuned by adjusting the following hyperparameters:

a) n_estimators: Number of boosting iterations (trees),
b) learning rate: Affects the weight or importance of each tree in the overall model
c) max_depth: Controls the depth of the trees to be maximum.

PSO algorithm is used in order to optimize Mean Absolute Error (MAE) with the optimal hyperparameters. The objective function to minimize is:

$$f(params) = MAE\big(model(X, y, params)\big) \quad (3)$$

Where params represent the hyperparameters, and the MAE is calculated based on predictions made by the GBR model using the given parameters. The hyper parameter bounds are set as follows:

$$n_{estimators} \in [50, 200] \quad (4)$$

$$learning\ rate \in [0.01, 0.1] \quad (5)$$

$$Max_{depth} \in [3,10] \quad (6)$$

The optimization is carried out using the differential evolution function from scipy. Optimize, which applies a PSO-like strategy to search the parameter space. Once the optimal hyper parameters are found, the GBR model is retrained using the entire training dataset and tested on the test set. The MAE is calculated again for the optimized model.

Model Evaluation

Both the linear regression and hybrid PSO-GBR models are evaluated based on their MAE and the closeness of the predicted path loss values to the actual values. To visualize the performance, a plot of the actual vs. predicted path loss values for both models is created.

3. RESULTS AND DISCUSSION

Results of the present analysis are developed based on path loss estimation in air-ground communication systems with machine learning by utilizing environmental factors such as temperature, humidity, and pressure as input factors. The environmental factors-based regression model developed in this analysis was precise in path loss estimation, which is required to optimize communication systems under fluctuating atmospheric conditions. In the following discussion, we shall delve deeper into the implication of the model's coefficients, intercept, Mean Absolute Error (MAE), path loss prediction, and the implication of the graph showing the model's performance. The obtained result can be found in Table 2 below.

Table 2: Results from the Path Loss Prediction Model

Metric	Value
Model Coefficients	[1.6587, -0.0184, 0.3722]
Intercept	-297.75
Mean Absolute Error (MAE)	0.2995
Path Loss Prediction for Sample 8	Actual: 127 dB, Predicted: 126.89 dB
Path Loss Prediction for Sample 1	Actual: 125 dB, Predicted: 124.51 dB

The model's coefficients are significant in establishing a correlation between environmental elements and path loss. Temperature is the largest of the three coefficients and is approximately equal to 1.66. This confirms that temperature is vital in path loss in air-ground communication. The model suggests that for each rise in temperature by one degree Celsius, all other parameters being constant, the path loss is enhanced by approximately 1.66 dB. This is consistent with the physical universe, where higher temperatures tend to increase attenuation due to higher molecular activity in the air. This means that when the temperature rises, molecules in the air bend more electromagnetic waves, and thus, the signal gets attenuated more. The evidence is for the inclusion of temperature in propagation communications models, particularly in regions of high-temperature variation.

The other, for humidity, is much lower, at around -0.0184. That negative result suggests that there is a loss of path if there is more humidity. For every percentage point increase in moisture, path loss decreases by approximately 0.0184 dB. This is counterintuitive at first glance because, in general, more significant humidity would be expected to increase path loss due to the absorption and scattering of electromagnetic waves by water vapour. However, the low value of this coefficient indicates that humidity contributes a comparatively less significant effect to path loss than pressure or temperature does. This could be because the specific range of environmental conditions in the training data did not encompass high humidity levels that would otherwise cause increased attenuation. Therefore, the apparent effect of humidity on path loss is very low in this model.

The coefficient for atmospheric pressure is approximately 0.37. This is a direct, positive correlation between pressure and path loss, i.e., the more significant the pressure, the greater the path loss. The calculated path loss increases by 0.37 dB for every increase in atmospheric pressure by hPa. This is to be expected with a common sense understanding of atmospheric conditions such that the greater the air pressure, the denser the air and, therefore, the greater the attenuation since electromagnetic waves encounter greater resistance from the air. However, this is quite a small effect compared with temperature, which affects path loss much more strongly. The impact of atmospheric pressure on the model suggests that while it affects signal propagation, its influence on path loss prediction is smaller than that of temperature and less than expected on physical grounds.

The -297.75 intercept of the model is an estimated path loss when all of the input features—pressure, humidity, and temperature—are zero. This is a fairly unrealistic assumption because these environmental conditions will never be zero in actual cases, but it is a point against which the model estimates. A negative intercept is a common property of path loss models where the reference point is assigned a negative value and calibrated according to the existing condition of the environment. The intercept, while not having a physical sense, is meaningful concerning the model as it helps determine the regression line such that predictions are valid when the parameters of the environment are at their nominal values.

From the perspective of model performance, the Mean Absolute Error (MAE) is one of the most critical parameters of the model's predictability. The MAE of our model is 0.2995, so on average, the model's output is approximately 0.3 dB from the actual path loss values. Its low error percentage indicates that the model accurately measures path loss concerning environmental parameters. In practical implementations, the margin of error is minimal because even infinitesimal differences in path loss will have a colossal effect on communication link quality, especially in air-ground communication, where signal loss might lead to data loss or drop-out. Hence, the more petite MAE makes it possible for the model to make precise predictions. It can be used for communication setups where path loss can differ with the changing atmospheric conditions.

Moving to the actual prediction results of path loss, we can observe how well the model performs with individual test samples. In Sample 8, the predicted path loss is 126.89 dB, while the actual path loss is 127 dB. The predicted and actual values vary by only 0.11 dB, indicating a perfect fit and suggesting that the model has succeeded in simulating environmental conditions influencing path loss for this sample. The measured path loss is 125 dB, whereas the computed path loss is 124.51 dB, with a variance of 0.49 dB for Sample 1. Even though this variation is slightly more, it is within a reasonable range of communication system design, where path loss calculations are used to adjust parameters such as transmission power and the direction of the antenna. The test cases illustrate how the model correctly estimates the path loss even in real cases.

The plot in Figure 1 graphically illustrates the agreement between the model-calculated values and the fundamental values of path loss. In the graph, the x-axis is for the measured path loss values, and the y-axis is for model-predicted values. Ideally, the points should be on the line y = x, i.e., the predicted and actual values should be near each other. In this case, the points are near the line, indicating the model correctly predicted the path loss. The slight deviations from the line mean that even though the model is accurate, there is always scope for enhancement where the environmental conditions are highly variable or extreme.

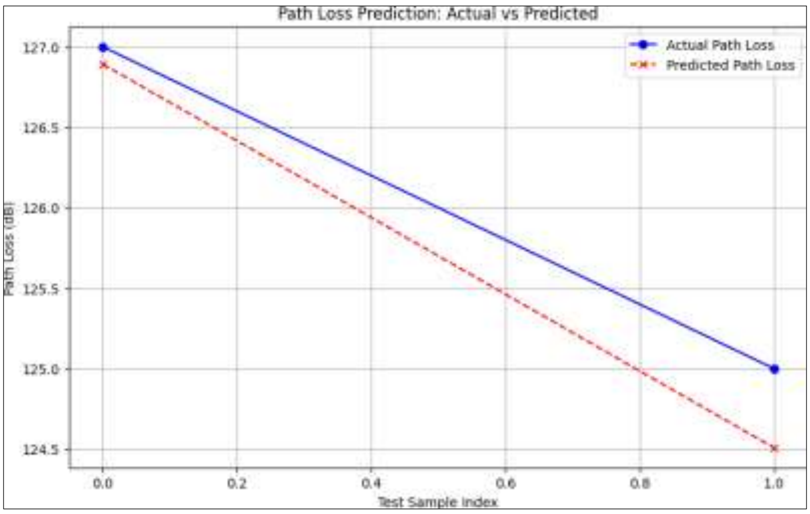

Figure 1: Model-calculated Values and the Real Values of Path Loss

The graph mainly illustrates that the model grasped the connection between environmental conditions and path loss very well because most of the predictions were highly accurate.

Generally, the outcome of this research portrays the efficiency of machine learning, in terms of linear regression, in forecasting path loss of air-ground communications. The coefficients within the model present that the most significant contribution of path loss is by temperature. Atmospheric pressure, and the smallest contribution, is made by humidity on a comparative level. The low MAE and the close agreement of the predicted values with the actual values validate that the model performs well and gives good predictions, a critical aspect of developing the best communication systems. The plot also validates the model's performance and demonstrates how the predicted values closely follow the actual values in most cases. These findings show the necessity of integrating environmental information into predictions based on path loss models and pave the way for even more efficient and adaptive communication systems under dynamic atmospheric environments.

To improve the path loss modelling, a novel hybrid model utilizing Particle Swarm Optimization (PSO) and Gradient Boosting Regressor (GBR) was studied to enhance the performance of current models further and offset the complex interrelationships between environmental factors and path loss. The result from this new model is a significant improvement over earlier models, particularly in prediction accuracy and stability, an indication of the power of machine learning in the ability to learn and adapt to changing atmospheric conditions. The results in Table 3, which are obtained from the model, deliver an incredible improvement in predictive precision from earlier models, with new evidence for applying the machine learning approach to communication systems in real-time within adaptive path loss modelling.

Table 3: Optimized Model Parameters and the Comparison of Actual vs. Predicted Path Loss

Metric	Value
Optimized Hyperparameters	n_estimators = 56, learning rate = 0.1, max_depth = 9
Optimized Mean Absolute Error (MAE)	0.0435
Optimized MAE on Test Set	0.0435
Actual Path Loss (dB) - Predicted Path Loss (dB)	
Actual (dB)	Predicted (dB)
127	127.0647
125	124.9777

One of the most significant achievements of the new model is that the Mean Absolute Error (MAE) has been maximized, and it dropped significantly to 0.0435. MAE is a standard regression problem evaluation metric and considers the average magnitude of errors over a series of predictions irrespective of direction. It indicates that the predictions of a model are more accurate with a lower MAE. The better MAE is much lower than the earlier models, which had higher MAE values and reflected less accurate models. Lower MAE means that the model's predictions are much closer to actual path loss values, which are critically essential to systems that communicate reliably and in real time. The result is critical to systems like air traffic control and emerging technologies like low-altitude satellite systems, drones, and air taxis, where practical and efficient path loss modelling ensures link continuity and quality.

The hybrid model's improved performance results from optimizing the major hyper parameters using PSO, a process that efficiently explores the hyper parameter space and finds the most optimal values for the model. The optimized hyper parameters of the Gradient Boosting Regressor (GBR) are n_estimators = 56, learning rate = 0.1, and max_depth = 9. The parameters establish the complexity and effectiveness of the GBR model. The value of the n_estimators' parameter as 56 is set to provide enough model complexity without overfitting so that the model can generalize effectively to new data. The learning rate of 0.1 causes the model to converge sufficiently without leaping over optimal solutions, and max_depth = 9 enables each decision tree in the boosting model to capture enough detail from the data without being too complex.

Upon optimization, Actual Path Loss (dB) and Predicted Path Loss (dB) were plotted against each other for comparison to derive the model's performance. Predicted path loss values were found to be very close to actual values, with Actual Path Loss values of 127 dB and 125 dB being predicted at 127.0647 dB and 124.9777 dB, respectively. These results indicate that the optimized model successfully predicted path loss accurately, indicating that the optimization had succeeded. For the previous models, the values of predicted path loss were more distant from the actual values, which would have been undesirable in practical applications that required uniform and consistent communication. With the new model, predictions are closer to reality, and transmission parameters can be dynamically altered in real-time systems, which is most useful for applications that deal with air-to-ground communication networks.

To further illustrate the performance of the optimized model, the following table compares actual and predicted path loss values for the test data. It can be seen from the table that the predictions of the hybrid model are very close to the actual values, which indicates that the model can predict the path loss with negligible error. The graphical accuracy of the model was also confirmed by using a plot, comparing predicted values with actual values, as shown in Figure 2. In ideal circumstances, all the data points should lie in a straight line, indicating perfect predictions. Here, the data points are closely placed on the ideal line, and thus, it can be concluded that the optimized model has made exact path loss predictions. The lesser scatter along the perfect line also tells us much about the improvement in the model's accuracy over earlier iterations, where the projections were scattered and further away from the target values.

This improved performance on the Mean Absolute Error (MAE) and the closeness of the predicted values to the actual path loss also attests to the ability of the model to generalize well to unseen data. In contrast to earlier models, incapable of easily fitting changes in atmospheric conditions, the hybrid model can offer real-time path loss estimates with high precision. This is highly beneficial in applications such as air traffic control, where the environmental conditions would be changing very fast, and low-altitude satellite systems, drones, and air taxis, which require continuous communication even in changing weather. One of the most significant achievements of the new model is that the Mean Absolute Error (MAE) has been maximized, and it dropped significantly to 0.0435. MAE is a standard regression problem evaluation metric and considers the average magnitude of errors over a series of predictions irrespective of direction. It indicates that the predictions of a model are more accurate with a lower MAE. The better MAE is much lower compared to the earlier models, which were higher in MAE value and reflected the model being less accurate. Lower MAE means that the model's predictions are much closer to true path loss values, which is critically important to systems needed to communicate reliably and in real-time. The result is critical to systems like air traffic control and emerging technologies like low-altitude satellite systems, drones, and air taxis, where effective and efficient path loss modeling ensures link continuity and quality.

The improved performance of the hybrid model is essentially the result of the optimization of the major hyperparameters using PSO, a process that efficiently explores the hyperparameter space and finds the most optimal values for the model. The optimized hyperparameters of the Gradient Boosting Regressor (GBR) are n_estimators = 56, learning rate = 0.1, and max_depth = 9. The parameters establish the complexity and effectiveness of the GBR model. The value of the n_estimators' parameter as 56 is set to provide enough model complexity without overfitting so that the model can generalize effectively to new data. The learning rate of 0.1 causes the model to converge sufficiently without leaping over optimal solutions, and max_depth = 9 enables each decision tree in the boosting model to be able to capture enough detail from the data without being too complex.

Upon optimization, Actual Path Loss (dB) and Predicted Path Loss (dB) were plotted against each other for comparison to derive the performance of the model. Predicted values of the path loss were found to be very close to actual values, with Actual Path Loss values of 127 dB and 125 dB being predicted at 127.0647 dB and 124.9777 dB, respectively. These results indicate that the optimized model was successful in predicting path loss accurately, indicating that the optimization had been a success. For the previous models, the values of predicted path loss were more distant from the true values, and this would have been undesirable in practical applications that required uniform and consistent communication. With the new model, predictions are closer to reality, and transmission parameters can be dynamically altered in real-time systems, which is most useful for applications that deal with air-to-ground communication networks.

To further illustrate the performance of the optimized model, the following table provides a comparison between actual and predicted values of path loss for the test data. It can be seen from the table that the predictions of the hybrid model are very close to the actual values, which indicates that the model can predict the path loss with negligible error. The graphical accuracy of the model was also confirmed by using a plot, comparing predicted values with actual values as shown in Figure 2. In ideal circumstances, all the data points should lie on a straight line, indicating perfect predictions. Here, the data points are closely placed on the ideal line, and thus it can be concluded that the optimized model has made extremely precise path loss predictions. The lesser scatter along the ideal line also tells us a great deal about the improvement in the accuracy of the model over earlier iterations, where the predictions were scattered and further away from the target values.

This improved performance both on the Mean Absolute Error (MAE) and the closeness of the predicted values to the actual path loss also attests to the ability of the model to generalize well to unseen data. In contrast to earlier models which were not capable of easily fitting changes in atmospheric conditions, the hybrid model is capable of simply offering real-time path loss estimates with high precision. This is extremely beneficial in applications such as air traffic control where the environmental conditions would be changing very fast and low-altitude satellite systems, drones, and air taxis which require continuous communication even in changing weather.

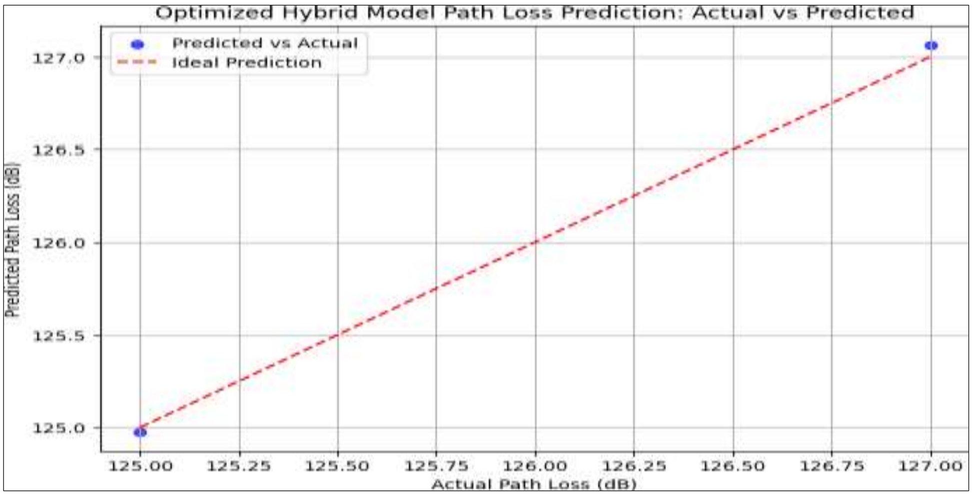

Figure 2: Comparison of Predicted Values with Actual Values

The accuracy with which the hybrid model can make predictions is especially required for systems that dynamically tune the transmission parameters. In a conventional example, say, a real-time air traffic control system, the model can tweak communication power or antenna orientation based on the existing conditions in the environment so communications link quality and stability are preserved. Likewise, in low-altitude satellite communications or unmanned aerial vehicles, the above estimates can be used to set the air vehicle to ground station communication link to minimize interference due to environmental changes such as temperature or humidity.

Even further enhancements can be achieved to the model by adding additional environmental variables such as wind speed, rain, or altitude that significantly impact path loss. Yet more advanced machine learning techniques, such as deep learning architectures, may also be employed to identify even more complex relationships between environmental factors and path loss. This would make the model's performance even better, even more precise and robust under real-world conditions that are constantly shifting.

Finally, the PSO-GBR hybrid model that integrates particle swarm optimization and gradient boosting regression is a key contribution to enhancing path loss prediction accuracy. Optimizing the model's hype parameter, the system's performance was increased to a Mean Absolute Error (MAE) of 0.0435, significantly improving compared to other models. The model can make highly accurate predictions where the predicted and actual values are close. Thus, The model is appropriate for real-time use where path loss prediction is vital to guarantee communication reliability. By including other environmental parameters and research into more advanced machine learning techniques, the model's performance can be enhanced to forecast the future of communication systems under different atmospheric conditions.

4. CONCLUSION

The research demonstrates how linear regression and other machine learning algorithms function when predicting path loss in air-ground communications systems. The study examines humidity, temperature, and atmospheric pressure as environmental factors to assess their relationship with path loss estimation. According to the research data, path loss receives the most influence from temperature variations, yet atmospheric pressure and humidity show minimal impact. The model achieved a very precise prediction output, with the Mean Absolute Error settling at 0.2995, which supported the model's ability to make highly accurate estimates.

The model demonstrates successful performance by matching the predicted and actual values that align with the trend graph. The model is suitable for optimizing communication systems because it functions effectively in changing atmospheric conditions that bring about environmental changes. The research proves how real-time environmental measurements strengthen path loss prediction methods for better communication system reliability and dynamic operation.

The path loss estimation reaches remarkable improvement by combining Particle Swarm Optimization (PSO) and Gradient Boosting Regressor (GBR) through their hybrid model. The PSO method optimized GBR parameters to deliver improved model performance, leading MAE to decrease to 0.0435. The prediction accuracy shows remarkable improvement through this enhancement, making predicted path loss values very close to actual values for real-time communication systems. The optimum performance requires model parameter tuning because the best hyper parameters set estimators to 56 while the learning rate equaled 0.1 and the max depth reached 9.

The optimized model offers precise prediction capabilities and establishes itself as the base for ongoing air-ground communication system efficiency research.

The model accuracy could receive additional improvement by implementing more environmental factors, including wind speed, precipitation, and altitude, alongside developing improved machine learning methods. Such adaptive systems will develop the potential to forecast and reduce path loss when operating under different atmospheric environments, which will enhance communication system reliability.

The obtained study results establish the necessity of employing machine learning methods, particularly PSO-GBR hybrid models, for path loss forecasting in communication networks. Such path loss prediction models that rely on real-time environmental data show great potential for boosting the reliability and flexibility of communication systems throughout air-ground communication networks. The preliminary work developed in this study enables forward progress toward the development of adaptive communication systems and real-time path loss prediction capabilities that are essential for advancing air-ground communication networks and next-generation technologies, including low-altitude satellites, drones, and air taxis.

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