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Urban LTE Radio Propagation Modeling Using Genetic Algorithm-Optimized Weighted Ensemble Learning

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ABSTRACT

Accurate path-loss prediction is essential for reliable LTE network planning, particularly in complex urban propagation scenarios where signal attenuation is influenced by radio, geometrical, and environmental factors. This study proposes a Genetic Algorithm (GA)-Based Weighted Blending framework for LTE path-loss prediction using real drive-test measurements collected along the Bus-Way corridor from Jembatan Ampera to Terminal Alang-Alang Lebar in Palembang City, Indonesia, at 1800 MHz and 2100 MHz. The dataset consisted of 19,766 cleaned samples with ten radio, geometrical, and environmental input features. Four heterogeneous machine-learning regressors, namely Random Forest, XGBoost, Multilayer Perceptron (MLP), and Support Vector Regression (SVR), were individually hyperparameter-tuned and combined through GA-based ensemble weight optimization using out-of-fold predictions. The proposed framework was evaluated against empirical propagation models, individual machine-learning models, and average blending using RMSE, MAE, R^2, and residual diagnostics. The results show that GA-Based Weighted Blending achieved the lowest numerical error among the evaluated models on the testing subset, with an RMSE of 5.5403 dB, MAE of 3.7150 dB, and R^2 of 0.7967. Compared with average blending, the proposed model reduced RMSE by approximately 2.08%. The optimized weights indicated that XGBoost and MLP provided the largest contribution within the ensemble, while lower-weight learners still contributed complementary prediction characteristics. However, the improvement over XGBoost was relatively small and not statistically significant, indicating that the proposed framework should be interpreted as an adaptive ensemble strategy rather than a definitive replacement for the strongest individual learner.

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1. INTRODUCTION

Accurate path loss prediction is a fundamental requirement in cellular network planning, as prediction errors can directly affect link budget estimation, base station (BS) configuration, coverage margin optimization, interference management, handover strategies, and overall network quality of service. However, in dense urban environments, particularly in LTE deployments, radio propagation represents a complex phenomenon that cannot be adequately characterized by distance and frequency parameters alone. The propagation behavior is influenced by the combined effects of network configurations and environmental characteristics, including antenna height variations, angular deviation from the serving cell's main beam, street orientation, building morphology, shadowing, scattering, and transitions between Line-of-Sight (LOS) and Non-Line-of-Sight (NLOS) conditions. The interaction among these factors introduces nonlinear variations and unpredictable fluctuations in signal attenuation. Consequently, two receiver locations with approximately the same distance from a base station may experience significantly different propagation conditions due to differences in surrounding environments and network geometries. This observation indicates that signal attenuation is determined not only by propagation distance but also by the complex interaction between environmental features and system configurations. Therefore, urban propagation environments cannot be accurately represented by a single deterministic attenuation curve. Measurement-based studies have demonstrated the importance of capturing realistic propagation characteristics; however, such approaches are often costly, highly dependent on measurement routes, and difficult to generalize across heterogeneous environments [1]–[5]. Similar challenges have been reported in various wireless communication systems, including cellular networks, vehicle-to-everything (V2X) communications, unmanned aerial vehicle (UAV) networks, LoRaWAN, and other urban wireless applications [6]–[15]. These findings highlight that the accuracy of a propagation model depends not only on the underlying mathematical formulation but also on its capability to effectively capture the spatial heterogeneity and complex interactions inherent in real-world propagation environments.

These limitations highlight the fundamental differences between empirical propagation models and data-driven approaches. Empirical models, such as COST-231 Hata, SUI, and ECC-33, provide several advantages, including computational efficiency, interpretability, and straightforward implementation in practical network planning. However, their predictive performance is inherently limited by predefined mathematical formulations and the specific propagation environments from which these models were derived. When actual deployment conditions differ from the original assumptions, such as variations in urban morphology, antenna configurations, obstruction characteristics, or propagation scenarios, significant prediction errors may occur, reducing their adaptability and generalization capability across diverse environments. In contrast, machine learning approaches do not depend on predefined propagation equations; instead, they learn complex nonlinear relationships directly from measurement data. This data-driven capability enables machine learning models to capture intricate propagation behaviors that are often difficult to describe using conventional empirical formulations. Consequently, various machine learning techniques, including artificial neural networks (ANN), Random Forest, XGBoost, and other advanced learning algorithms, have demonstrated promising results across a wide range of propagation scenarios, including multi-frequency environments, dense urban areas, indoor and enclosed spaces, tropical regions, vehicular communications, and modern cellular networks [5]–[8], [16]–[26]. Nevertheless, the effectiveness of machine learning-based propagation modeling is not guaranteed solely by the choice of algorithm. Model performance strongly depends on the representativeness of the training dataset, the relevance and quality of input features, the consistency of data preprocessing, and the robustness of validation strategies used to avoid overfitting and inflated performance estimates. Therefore, the research direction in propagation modeling has gradually evolved from simply demonstrating the capability of machine learning to fit measured propagation data toward developing data-driven frameworks that provide reliable generalization, rigorous validation, and robust prediction performance under previously unseen propagation conditions.

Research on machine learning-based radio propagation modeling has experienced a significant evolution in methodology. Early studies mainly focused on identifying a single optimal regressor capable of achieving the lowest RMSE or MAE values. However, recent research has increasingly shifted toward more flexible and robust approaches, including ensemble learning, multimodal modeling, radio-map learning, graph-based learning, and generative methods [1], [18], [23], [24], [27]–[35]. This shift is motivated by the inherent complexity of radio propagation, which is governed by the interaction of multiple environmental, geometric, and network-related factors that are often difficult to capture using a single learning algorithm. Each machine learning technique provides different representation capabilities for extracting patterns from propagation data. Tree-based learners are effective in modeling nonlinear relationships, feature interactions, and complex decision boundaries; kernel-based methods are capable of representing nonlinear structures in high-dimensional feature spaces; while artificial neural networks can approximate complex multivariate relationships when sufficient training data are available. These differences lead to distinct prediction behaviors and error characteristics among individual models, suggesting that combining multiple learners may provide more stable and reliable predictions than relying on a single model. Therefore, ensemble learning is not merely a mechanism for aggregating predictions but also a modeling strategy that exploits the complementary strengths of heterogeneous learners to improve robustness and generalization capability. Studies on neural network ensembles, heterogeneous machine learning ensembles, spatial radio-map learning, and stacking approaches have demonstrated that model diversity plays an essential role in enhancing propagation prediction accuracy [1], [18], [23], [27]–[35]. Nevertheless, improvements in model performance are influenced not only by the choice of algorithms but also by the quality of input features, measurement data distribution, propagation environment characteristics, and the rigor of the validation methodology. Research conducted in urban canyon environments, vehicular communication systems, UAV-based networks, and LoRa applications [9]–[15], [22], [36] further indicates that ensemble model development is an integral component of the propagation modeling process rather than merely a final step for combining prediction outputs. The selection of appropriate base learners and the design of effective combination strategies ultimately determine the accuracy, stability, and generalization capability of the resulting model under diverse radio propagation conditions..

The heterogeneous characteristics of these models reveal an unresolved challenge in many ensemble approaches applied to radio propagation modeling. Conventional averaging methods assume that all constituent models have equal importance by assigning identical weights to each predictor, regardless of differences in predictive capability, model reliability, or error characteristics. Although this strategy can be effective when individual models exhibit comparable accuracy and generate complementary prediction errors, such assumptions are often unrealistic in heterogeneous radio propagation regression problems. Different algorithms may respond differently to variations in environmental conditions, data distributions, and feature representations, resulting in unequal predictive contributions among models. Consequently, assigning uniform weights may allow less accurate or redundant predictors to reduce the overall effectiveness of the ensemble, rather than enhancing the information provided by stronger models. Conversely, relying solely on the best-performing individual model may also be suboptimal because it ignores complementary information embedded in other models with different prediction behaviors. Therefore, the fundamental challenge in ensemble-based propagation modeling is not simply determining whether multiple models should be combined, but rather identifying how the contribution of each model can be optimized according to its predictive capability and error characteristics. Adaptive weighted ensemble strategies provide a potential solution by allowing each predictor to contribute proportionally based on its reliability while preserving the diversity of information offered by heterogeneous learning algorithms. This challenge becomes increasingly important when base learners have been independently optimized through hyperparameter tuning, as such optimization processes may further increase variations in model performance, complexity, and residual patterns. Hence, an effective weight optimization mechanism is required to adaptively identify the optimal combination of heterogeneous predictors, thereby producing propagation models with improved accuracy, robustness, and generalization capability under diverse radio environments.

Another important limitation relates to external validity and the generalization capability of propagation models. Models developed using measurement data collected from specific environments—such as a particular city, measurement route, frequency band, or cell configuration—cannot be directly assumed to maintain similar performance when applied to different propagation scenarios. Therefore, the contribution of measurement-based studies should not be limited to demonstrating that one algorithm outperforms others universally; instead, such studies should investigate the effectiveness of a given methodological approach within clearly defined propagation environments and identify the factors that influence its performance. In the urban environment of Palembang, previous measurement-based research demonstrated that a Random Forest model could improve path loss prediction accuracy using drive-test measurements [37]. This finding highlights the potential of data-driven approaches for capturing local radio propagation characteristics. However, it also raises a fundamental research question: are the observed performance improvements primarily attributed to the selection of the best individual learner, or do multiple heterogeneous predictors with different learning behaviors contain complementary information that can be effectively integrated to achieve better predictive performance? Addressing this question requires further investigation into adaptive model combination strategies that can exploit predictor diversity, rather than relying solely on fixed-weight ensemble schemes or selecting a single optimal model. Such strategies are essential for developing propagation models with improved robustness and generalization capability across varying radio environments.

The present study responds to these gaps by developing a Genetic Algorithm-Optimized Weighted Ensemble Learning framework for LTE path-loss prediction using real drive-test measurements collected in Palembang, Indonesia. The proposed framework integrates four heterogeneous machine-learning base learners, namely Random Forest, XGBoost, Multilayer Perceptron (MLP), and Support Vector Regression (SVR), where each learner undergoes individual hyperparameter tuning through an exhaustive search procedure to identify suitable model configurations. Following this optimization stage, the tuned learners are combined using a Genetic Algorithm (GA)-based weighting mechanism. Rather than assigning identical importance to all predictors, GA determines the optimal contribution of each learner by searching for a convex combination of out-of-fold predictions that minimizes ensemble validation error. This strategy enables the ensemble to exploit complementary predictive characteristics among heterogeneous learners while reducing the influence of models that provide limited additional information. . . The contribution of this work does not originate from the use of Genetic Algorithm itself, as evolutionary optimization techniques have been widely investigated. Instead, the methodological contribution lies in applying GA-based adaptive weighting to address a specific challenge in urban LTE propagation modeling: determining how individually tuned heterogeneous predictors should contribute when their predictive capability and error characteristics are not identical. The proposed framework integrates three essential components: (1) independently hyperparameter-tuned heterogeneous regression learners, (2) out-of-fold prediction-based ensemble construction to reduce information leakage during weight estimation, and (3) statistical interpretation of performance improvement using real urban LTE drive-test measurements. Compared with studies focusing on individual models, fixed-weight ensembles, neural-network-only combinations, or radio-map learning frameworks [1], [18], [27], [23], [28], [31], [34], this study emphasizes adaptive learner contribution and evaluates whether the obtained improvement is empirically and statistically defensible rather than relying solely on marginal reductions in prediction error.

2. METHOD

2.1. Research Framework

The research framework was designed to systematically develop and evaluate an adaptive ensemble-learning approach for LTE path-loss prediction using real drive-test measurements collected along the Bus-Way corridor in Palembang City, Indonesia. The framework integrates data preparation, individual hyperparameter tuning of heterogeneous machine-learning base learners, out-of-fold prediction generation, Genetic Algorithm (GA)-based ensemble-weight optimization, and comparative model evaluation. The overall workflow was structured to distinguish the development and optimization stages from the subsequent prediction and performance assessment, while ensuring that the contribution of each base learner to the final ensemble could be explicitly evaluated. The complete research workflow is presented in Figure 1.

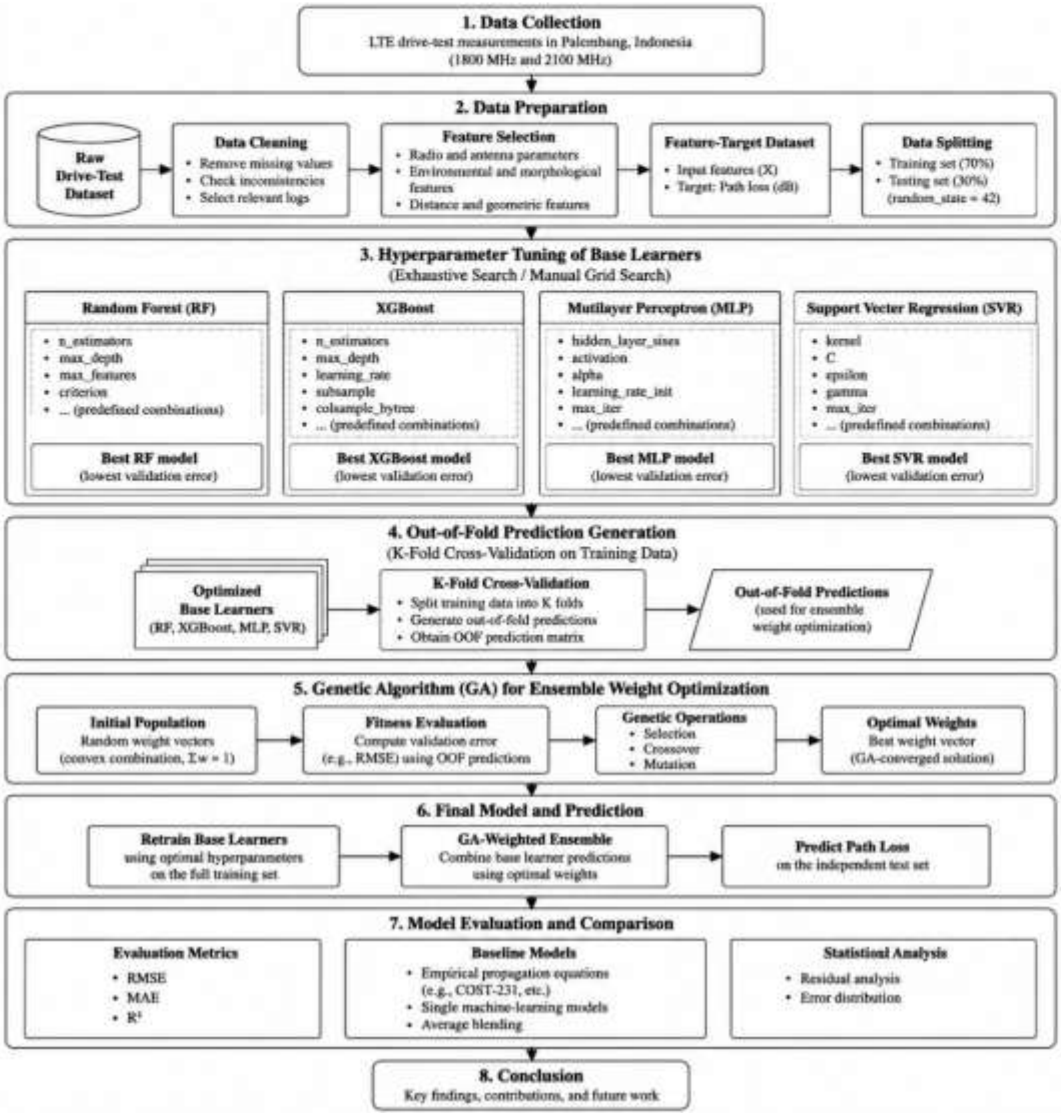

Figure 1. The proposed framework for GA-optimized weighted ensemble learning in LTE path-loss prediction

The research framework consisted of seven sequential stages. First, LTE drive-test measurements were collected along the investigated Bus-Way corridor in Palembang City, Indonesia. Second, the collected data were cleaned, processed, and transformed into input–output variables for supervised path-loss regression.

Third, four heterogeneous machine-learning base learners, namely Random Forest, XGBoost, Multilayer Perceptron (MLP), and Support Vector Regression (SVR), were individually tuned using predefined hyperparameter search spaces. Fourth, out-of-fold predictions were generated from the selected base learners using training-data cross-validation. Fifth, the Genetic Algorithm (GA) was applied to optimize the ensemble weight vector based on the RMSE minimization objective. Sixth, the final GA-Based Weighted Blending model was constructed by combining the base-learner predictions using the optimized weights. Finally, all models were evaluated and compared using RMSE, MAE, R^2, and residual diagnostics.

This framework was selected because urban path loss is rarely governed by a single linear attenuation mechanism. Instead, it is shaped by interacting radio-frequency, geometrical, and environmental factors, including frequency band, antenna height, angular displacement, building morphology, route width, and serving-cell distance. Therefore, the methodology combined interpretable empirical baselines with flexible nonlinear machine-learning models and an adaptive ensemble mechanism.

The complete experimental workflow was executed sequentially to preserve separation between model development and final testing. After measurement cleaning and predictor construction, the dataset was divided into training and testing subsets using a 70:30 ratio. Each candidate hyperparameter configuration was fitted using the training subset and evaluated on the testing subset to identify the best-performing configuration for each base learner. The selected base learners were subsequently used to generate out-of-fold predictions on the training subset, ensuring that each training observation used for ensemble-weight estimation was predicted by a model that had not been fitted to that observation. The GA optimized a nonnegative weight vector whose elements summed to one by minimizing the RMSE of these out-of-fold blended predictions. Finally, each base learner was refitted on the full training subset, the optimized weights were applied to their hold-out predictions, and the resulting ensemble was compared with empirical models, individual learners, and equal-weight blending. This sequence was used instead of a schematic workflow figure so that every stage, data boundary, and leakage-control step is explicitly documented in the text.

2.2. Dataset and Predictor Structure

The dataset was obtained from a drive-test measurement campaign conducted along the route from Jembatan Ampera to Terminal Alang-Alang Lebar in Palembang City. This route represents an urban propagation corridor with variations in road width, building height, inter-building distance, antenna geometry, and serving-cell distance. Measurements were collected at two LTE frequency bands, namely 1800 MHz and 2100 MHz. The target variable was physical uplink control channel (PUCCH) path loss, while the input variables represented radio, geometrical, and environmental characteristics of the measurement route.

The initial dataset contained 19,963 samples and 11 variables. After removing incomplete observations, 19,766 complete samples were retained. The cleaned dataset was divided into 13,836 training samples and 5,930 testing samples using a 70:30 split. During base-learner hyperparameter tuning, each candidate configuration was fitted to the training subset and evaluated on the testing subset to identify the best-performing configuration. The selected base learners were subsequently used to generate out-of-fold predictions on the training subset for GA-based ensemble-weight optimization.

Table 1. Dataset characteristics and experimental data structure

Component	Value / Information
Collection method	Drive-test measurement
Route	Jembatan Ampera to Terminal Alang-Alang Lebar, Palembang City
Frequency bands	1800 MHz and 2100 MHz
Initial dataset	19,963 samples × 11 variables
Incomplete records	197 records in each angular variable
Cleaned dataset	19,766 complete samples × 11 variables
Training subset	13,836 samples
Testing subset	5,930 samples
Prediction target	PUCCH path loss (dB)

The selected features were designed to represent both physical propagation variables and local urban morphology. Frequency and serving-cell distance represent radio-domain attenuation factors. Transmitter and receiver height variables capture the vertical geometry of the link. Vertical and horizontal angular displacement describe the relative receiver position from the transmitter main beam. Route width, building height, and inter-building distance represent environmental obstruction and urban morphology. This feature combination was selected to enable the model to learn nonlinear path-loss behavior beyond the assumptions of conventional empirical equations.

The ten predictors were Frequency (MHz), Total Height of TX (m), Total Height of RX (m), Delta Height of TX-RX (m), vertical angle of the receiver from the transmitter main beam (degree), horizontal angle of the receiver from the transmitter main beam (degree), route width (m), total building height (m), distance between buildings (m), and LTE serving-cell distance (m). Frequency and serving-cell distance represent basic radio attenuation factors; the transmitter height, receiver height, and TX–RX height difference characterize the vertical geometry of the radio link; the two angular variables describe receiver displacement from the serving antenna main beam; and route width, building height, and inter-building distance characterize local urban morphology. PUCCH path loss in dB was the single regression output.

2.3. Preprocessing, Baselines, and Base Learners

The preprocessing stage consisted of missing-value inspection, data cleaning, input–output construction, train-test splitting, and model-specific scaling. Missing-value inspection showed incomplete records only in the vertical and horizontal angular variables. Since the number of incomplete observations was relatively small compared with the total dataset size, listwise deletion was applied. This decision retained a large final sample size while avoiding imputation bias in angular features that are physically meaningful for antenna-mainbeam alignment.

After cleaning, the predictor matrix was constructed from the ten input variables described above, while PUCCH path loss was used as the regression target. The dataset was then divided into training and testing subsets using a 70:30 split. During base-learner hyperparameter tuning, candidate configurations were fitted using the training subset and evaluated using the testing subset. The selected base learners were subsequently used to generate out-of-fold predictions on the training subset for GA-based ensemble-weight optimization. Feature standardization was applied to MLP and SVR because these algorithms are sensitive to feature scale. Tree-based models, namely Random Forest and XGBoost, were trained without feature scaling because tree-splitting procedures are generally insensitive to predictor scaling.

Three empirical propagation models were included as conventional baselines: COST-231 Hata, SUI, and ECC-33. These models were used to provide a reference against classical fixed-form propagation equations. Their inclusion was necessary to evaluate whether data-driven models offer meaningful improvement over established wireless propagation baselines.

Four optimized machine-learning models were used as base learners: Random Forest, XGBoost, MLP, and SVR. These models were selected because they represent different learning mechanisms. Random Forest represents bagging-based tree ensembles; XGBoost represents gradient-boosted decision trees; MLP represents neural nonlinear approximation; and SVR represents kernel-based nonlinear regression. The proposed model combines these base learners using GA-Based Weighted Blending. The blended prediction is defined in (1), where each weight is nonnegative and the weights sum to one. The purpose of GA optimization was to avoid the limitation of equal-weight averaging, where weak or redundant learners may degrade ensemble performance.

2.4. Hyperparameter Optimization and GA-Based Blending

Each base learner was individually hyperparameter-tuned before being used in the blending framework. Hyperparameter tuning was conducted to identify suitable configurations for each base learner and to avoid relying on arbitrary default settings. The principal search spaces and best configurations are summarized in Table 2. The MLP configuration used two hidden layers to capture nonlinear propagation patterns while maintaining a controlled model size. The XGBoost configuration used a moderate learning rate and relatively deep trees to capture feature interactions. Random Forest used restricted tree depth to reduce overfitting, while SVR used an RBF kernel to model nonlinear relationships after feature standardization.

The GA was used to optimize the weight vector assigned to the base learners. Each chromosome represented a four-dimensional vector containing the weights for Random Forest, XGBoost, MLP, and SVR. The fitness function was defined as the RMSE between the blended out-of-fold prediction and the observed target value in the training set. The GA searched for the weight combination that minimized this RMSE.

The general GA procedure consisted of population initialization, fitness evaluation, parent selection, crossover, mutation, weight normalization, and convergence monitoring. Each chromosome represented a candidate weight vector for the four base learners. Candidate weights were constrained to be nonnegative and were normalized so that their sum equaled one, thereby preserving the ensemble as a convex combination of the base-learner predictions.

For a candidate weight vector $W = \omega_{RF}, \omega_{XGB}, \omega_{MLP}, \omega_{SVR}$ the ensemble prediction for the (i)-th observation was defined as

$$\hat{y}_{ens,i} = \sum_{j=1}^{4} \omega_j \hat{y}_{ij}$$

subject to

$$\omega_j \geq 0$$

$$\sum_{j=1}^{4} \omega_j = 1$$

The GA objective was to identify the optimal weight vector that minimized the RMSE of the blended out-of-fold predictions over the training subset:

$$W = argmin \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(yi - \sum_{j=1}^{4} \omega_j \hat{y}_{ij}{}^{OOF}\right)^2}$$

The resulting optimal weights were subsequently applied to the predictions of the four selected base learners to obtain the final weighted-ensemble prediction.

Table 2. Hyperparameter search spaces and selected base-learner configurations

Base Learner	Search Space	Selected Configuration
Random Forest	n_estimators: 100, 200, 300, 500; max_depth: None, 5, 10, 15, 20, 25; max_features: auto, sqrt, log2	300 trees; max_depth = 10; max_features = sqrt; squared_error
XGBoost	n_estimators: 50–500; max_depth: 1–8; learning_rate: 0.01–0.20; subsample: 0.7–1.0; colsample_bytree: 0.7–1.0	150 trees; max_depth = 8; learning_rate = 0.05; subsample = 1.0; colsample_bytree = 0.7
MLP	max_iter: 1000, 1500; hidden layers: (50), (100), (50,30), (100,50); activation: relu/tanh; alpha: 0.0001/0.001	max_iter = 1000; hidden layers = (100,50); tanh; adam; alpha = 0.0001; learning_rate_init = 0.001
SVR	kernel: linear/poly/rbf/sigmoid; C: 0.1–100; epsilon: 0.01–0.20; gamma: scale/auto; max_iter: 1000–20000	RBF; C = 100; epsilon = 0.1; gamma = scale; max_iter = 20000

2.5. Training, Validation, and Evaluation

The training and testing strategy consisted of two evaluation layers. First, out-of-fold validation was performed on the training set to generate out-of-sample predictions from each base learner. In this process, each training sample was predicted by a model that had not been trained on that sample. These out-of-fold predictions were then used as inputs to the GA optimization procedure. This design reduced the risk of data leakage during ensemble-weight estimation.

Second, after the optimal ensemble weights were obtained, each selected base learner was retrained using the full training set. The retrained models then generated predictions for the testing subset. The final GA-Based Weighted Blending prediction was computed by applying the GA-optimized weights to the testing-subset predictions of the four base learners. The testing subset was not used for out-of-fold prediction generation or GA-based ensemble-weight optimization, although it had been used previously to assess candidate hyperparameter configurations during base-learner tuning.

The models were evaluated using RMSE, MAE, and R^2. RMSE was used because it penalizes large prediction errors and is sensitive to severe path-loss deviations. MAE was used because it provides an interpretable average error in dB. R^2 was used to measure the proportion of path-loss variance explained by each model.

The experiment was implemented using a Python-based machine-learning environment. Data handling and numerical computation were performed using Pandas and NumPy. Machine-learning models, preprocessing, validation, and evaluation metrics were implemented using Scikit-learn. XGBoost was implemented using the XGBoost library, and the GA was implemented in a Python evolutionary-computation environment. Diagnostic visualizations were generated using Matplotlib. To ensure reproducibility, random seeds were fixed for train-test splitting, model initialization, and GA evolution.

3. RESULTS AND DISCUSSION

3.1. Empirical Patterns and Predictor Diagnostics

The experimental results show a clear hierarchy among the evaluated models. The empirical propagation models produced substantially larger errors than all machine-learning models, indicating that fixed-form propagation equations were unable to represent the local propagation characteristics of the measured Palembang urban corridor. Among the data-driven models, XGBoost and MLP were the strongest individual predictors, while Random Forest and SVR showed weaker predictive accuracy. The proposed GA-Based Weighted Blending model achieved the lowest numerical error among the evaluated models, however,

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the improvement over XGBoost was marginal and statistically non-significant. This distinction is important because it positions the proposed model as an adaptive and robust ensemble strategy rather than as a model that decisively replaces the best single learner.

The feature-correlation matrix provides diagnostic evidence that the predictor set contains both overlapping and complementary information. The strongest visible association occurs between transmitter height and transmitter-receiver height difference, while most environmental and angular variables show substantially weaker pairwise correlations with PUCCH path loss. This pattern indicates that no single input provides a complete linear explanation of the measured attenuation. Instead, the target is influenced by multiple radio-geometrical and morphology-related variables whose effects are partly nonlinear and interaction-dependent. Such a structure supports the use of flexible regressors and ensemble learning, because highly nonlinear learners can combine weak individual relationships that would be difficult to represent with a single fixed empirical equation.

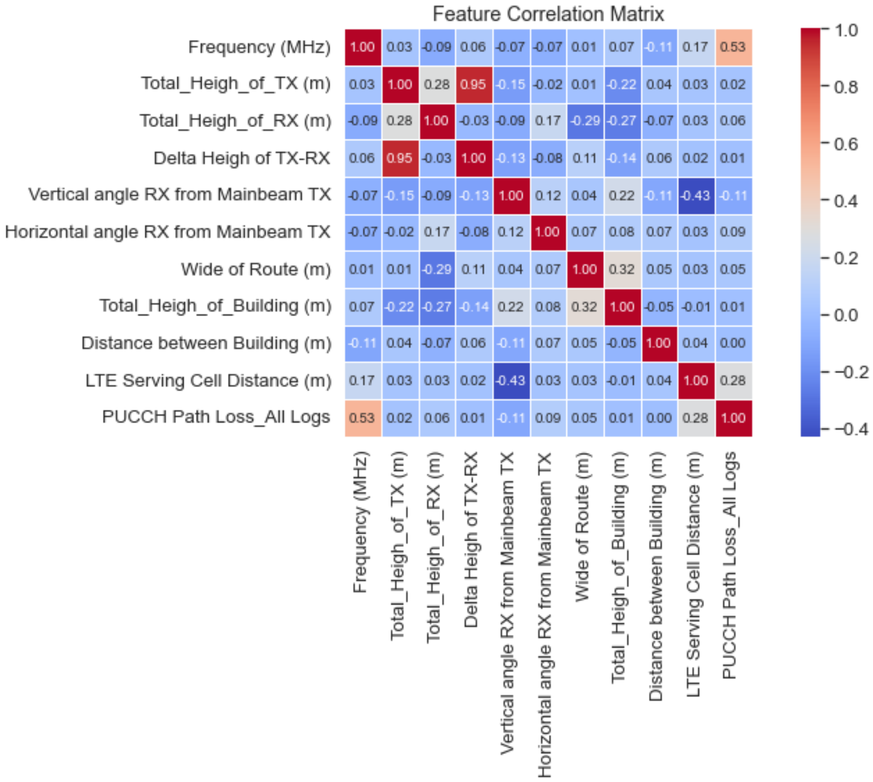


Figure 1. Feature correlation matrix for the cleaned urban LTE drive-test dataset.

3.2. Out-of-Fold Validation and Ensemble-Weight Behavior

The out-of-fold validation results provide the first quantitative evidence that adaptive blending improves internal predictive stability. As shown in Table 3, MLP achieved the best out-of-fold RMSE among the individual base learners, followed closely by XGBoost. Random Forest and SVR produced larger errors, suggesting that their predictive structures were less suitable for the most complex propagation variations in this dataset. Average Blending produced a slight improvement over individual models, but the proposed GA-Based Weighted Blending achieved the best out-of-fold performance.

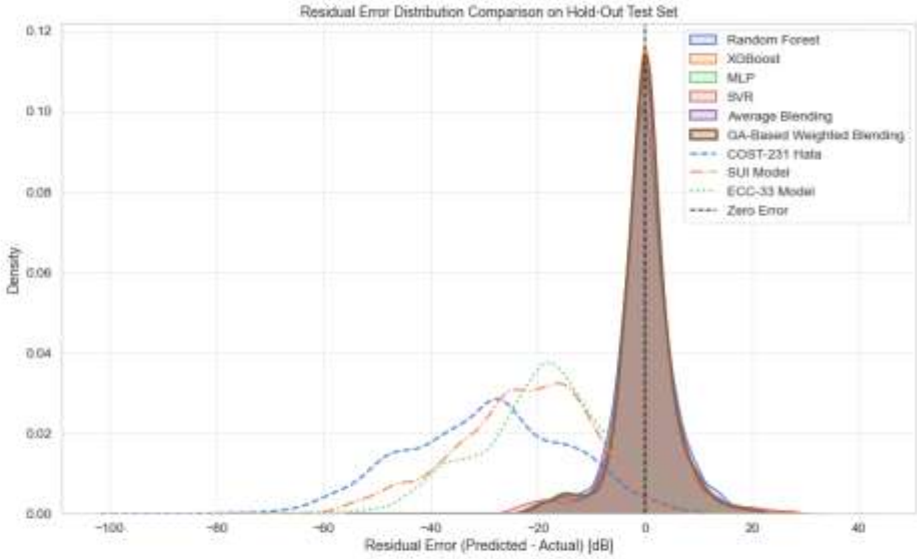
The GA-optimized weights provide an important interpretive result. The final weights were 0.0242 for Random Forest, 0.4594 for XGBoost, 0.5074 for MLP, and 0.0090 for SVR. More than 96% of the ensemble contribution was assigned to XGBoost and MLP. This outcome indicates that the GA did not simply assign equal importance to all base learners; instead, it adaptively adjusted learner contributions according to their predictive complementarity, error characteristics, and contribution to minimizing the ensemble objective function. The result also suggests that XGBoost and MLP captured complementary aspects of urban path loss. XGBoost likely modeled threshold-like feature interactions, while MLP approximated smoother nonlinear relationships among scaled predictors.

Table 3. Out-of-fold performance of base learners and blending models

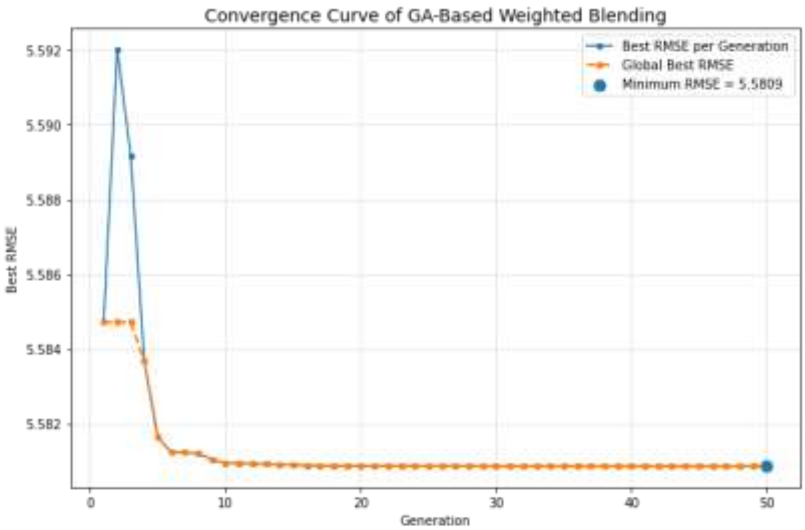
Category	Model	OOF RMSE	OOF MAE	OOF R^2
Base Learner	Random Forest	5.9330	4.1663	0.7685
Base Learner	XGBoost	5.6870	3.7981	0.7873

Category	Model	OOF RMSE	OOF MAE	OOF R²
Base Learner	MLP	5.6747	3.8713	0.7882
Base Learner	SVR	6.2817	4.0911	0.7405
Simple Ensemble	Average Blending	5.6633	3.8272	0.7891
Proposed Ensemble	GA-Based Weighted Blending	5.5809	3.7617	0.7952

The residual error and GA convergence diagnostics in **Figure 2** provide evidence regarding the optimization behavior and prediction error characteristics of the proposed ensemble. The convergence curve indicates that the GA optimization reached a stable solution within the performed run, with the best RMSE achieved at generation 50. Nevertheless, because GA optimization is stochastic, convergence in a single run does not guarantee global optimality or weight robustness. Future studies should repeat the optimization using multiple random seeds and independent runs to assess the variability of the obtained weights.



(a)



(b)

Figure 2. Learning diagnostics: (a) residual error distributions on the hold-out test set and (b) GA convergence behavior

3.3. Final Hold-Out Performance

The hold-out test results confirm the superiority of machine-learning models over empirical propagation baselines. As shown in Table 4, the proposed GA-Based Weighted Blending model achieved the lowest RMSE of 5.5403 dB, the lowest MAE of 3.7150 dB, and the highest R^2 of 0.7967. XGBoost was the strongest single model, with RMSE of 5.5872 dB and MAE of 3.7247 dB. MLP performed closely behind XGBoost, while Random Forest and SVR were less competitive.

The comparison with Average Blending demonstrates the benefit of adaptive weighting. GA-Based Weighted Blending reduced RMSE by approximately 2.08% and MAE by approximately 1.94% relative to

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equal-weight averaging. This improvement is modest but meaningful because both ensemble models were built from the same base predictions. Therefore, the improvement can be attributed to optimized weight allocation rather than to additional input features or model classes.

The improvement over empirical models was much larger. Relative to COST-231 Hata, the proposed model reduced RMSE by approximately 83.26% and MAE by approximately 87.45%. Relative to SUI, it reduced RMSE by approximately 78.82% and MAE by approximately 83.97%. Relative to ECC-33, it reduced RMSE by approximately 75.27% and MAE by approximately 80.71%. These large reductions show that the default empirical models were poorly matched to the local urban morphology and antenna geometry of the measured route. Figure 3 shows that the data-driven predictions follow the ideal one-to-one tendency over the principal path-loss range, although dispersion remains visible at the extremes where fewer observations are available.

Table 4. Final hold-out test performance of empirical, machine-learning, and ensemble models

Model	Test RMSE	Test MAE	Test R^2
COST-231 Hata	33.0951	29.6061	-6.2537
SUI	26.1614	23.1784	-3.5327
ECC-33	22.3994	19.2603	-2.3228
Random Forest	5.8954	4.1014	0.7698
XGBoost	5.5872	3.7247	0.7933
MLP	5.6113	3.7895	0.7915
SVR	6.2966	4.0659	0.7374
Average Blending	5.6577	3.7884	0.7880
GA-Based Weighted Blending	5.5403	3.7150	0.7967

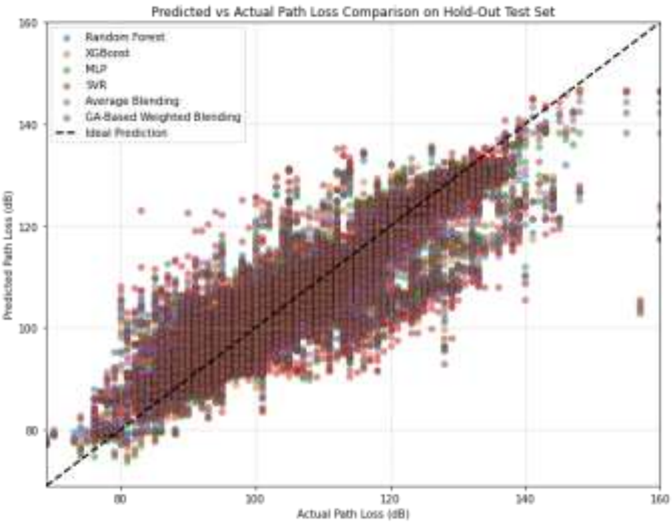

Figure 3. Predicted versus actual path loss for the evaluated data-driven models on the hold-out test set

3.4. Statistical Significance, Residual Behavior, and Robustness

Pairwise error testing strengthens the interpretation of the numerical ranking. After Holm correction, GA-Based Weighted Blending showed statistically significant lower absolute error than Average Blending (adjusted $p = 2.39 \times 10^{-10}$), MLP (1.86×10^{-12}), Random Forest (3.46×10^{-69}), SVR (1.77×10^{-26}), and all three empirical propagation models (adjusted p values effectively zero at the reported precision). In contrast, the comparison with XGBoost was not statistically significant (adjusted $p = 0.906831$). The best numerical score therefore does not justify a claim of universal statistical superiority over the strongest single learner.

The non-significant difference against XGBoost means that the proposed model should not be described as statistically superior to all individual learners. Instead, the stronger and more defensible claim is that GA-Based Weighted Blending provides the best numerical performance and significantly improves over most baselines, while offering an adaptive ensemble mechanism that reduces dependence on a single learner. From a practical perspective, this may still be valuable in network-planning applications where robustness and stability are preferred over reliance on one model. However, if computational simplicity is prioritized, XGBoost remains a highly competitive alternative.

Residual behavior provides information beyond aggregate RMSE and MAE. The residual-density comparison shows that the machine-learning and ensemble models concentrate their errors much more tightly around zero than the empirical models, whose residual distributions are broader and substantially displaced.

This indicates that the data-driven methods better capture the local path-loss level of the measured corridor, whereas the standard empirical equations exhibit systematic mismatch. The ensemble residual profile is similar to those of XGBoost and MLP, which is consistent with the GA weight distribution and with the small performance difference among these three predictors. Residual concentration alone, however, does not establish generalization beyond the measured route, so the result must be interpreted together with the validation design and the study limitations.

Several limitations should be acknowledged. First, the dataset was collected along a specific urban route, so the model's validity is strongest for similar propagation conditions and should not be generalized directly to other cities or environments without further testing. Second, random train-test splitting may inflate performance if spatially adjacent drive-test samples appear in both training and testing subsets. Third, the pairwise t-test assumes independent errors, an assumption that may be weakened by spatial autocorrelation in sequential drive-test measurements. Fourth, the empirical models appear to have been evaluated in their standard forms; locally calibrated empirical baselines would provide a stricter comparison. Fifth, the GA search should be repeated across multiple random seeds to verify weight stability.

3.5. Comparison with Previous Studies and Practical Implications

The results are consistent with recent artificial intelligence-based path-loss prediction studies. Sukemi et al. [37] showed that Random Forest can improve path-loss prediction accuracy in the Palembang City area, particularly after hyperparameter tuning. The present study extends this local evidence by comparing multiple empirical, single machine-learning, and ensemble models, and by introducing GA-based adaptive weighting.

The importance of nonlinear and multi-frequency learning is also supported by Nguyen and Cheema [5], who proposed a deep-neural-network-based multi-frequency path-loss model, and by Faruk et al. [16], who developed an ANN-based multiband path-loss model for built-up environments. These studies align with the present finding that MLP received the largest GA weight and contributed strongly to ensemble performance. The superiority of machine-learning models over uncalibrated empirical baselines is consistent with Famoriji and Shongwe [19], who showed that machine-learning-based methods can provide effective path-loss prediction in environment-specific conditions. However, the present results should not be interpreted as proving that empirical models are universally poor. Rather, they show that the default COST-231 Hata, SUI, and ECC-33 formulations were not suitable for the specific Palembang route without local calibration.

The ensemble-learning contribution is supported by Kwon and Son [1] and Elmezughi et al. [18], who showed that ensemble-based learning can improve prediction stability in wireless propagation modeling. The present study differs by using GA-based continuous weighting across heterogeneous learners rather than combining only neural-network architectures. The strong role of XGBoost is consistent with Iliev et al. [2], Xu et al. [3], and Ben Ameur et al. [4], who demonstrated the effectiveness of XGBoost or hybrid machine-learning approaches in path-loss prediction. The present study contributes to this literature by showing that even when GA-Based Weighted Blending achieves the best numerical result, XGBoost remains statistically competitive.

Theoretically, the findings support the view that urban path loss is better modeled as a nonlinear, environment-dependent mapping than as a fixed empirical function. The dominance of XGBoost and MLP in the GA weight distribution indicates that both tree-based feature partitioning and neural nonlinear approximation are useful for representing urban LTE propagation. The near-zero weights assigned to Random Forest and SVR show that ensemble learning should not assume equal contribution from all learners.

Practically, the proposed framework can support urban LTE and future 5G network planning by improving path-loss estimation accuracy. Lower prediction error can improve link-budget estimation, weak-coverage detection, antenna planning, interference assessment, and cell-edge performance analysis. Nevertheless, because the dataset is route-specific, operational deployment should be preceded by validation across additional routes, base-station sectors, time periods, and urban morphologies.

3.6. Research Extensions

Future studies should strengthen the external validity of the proposed approach by adopting spatially aware validation strategies such as route-block splitting, leave-cell-out validation, and cross-city testing. Explainable artificial intelligence methods such as SHAP, permutation importance, and partial dependence analysis should also be incorporated to identify the physical contribution of frequency, distance, antenna geometry, and building morphology. In addition, spatio-temporal models such as long short-term memory networks, temporal convolutional networks, graph neural networks, and transformer-based architectures could be explored to capture sequential drive-test dependencies.

A promising future direction is to develop physics-informed hybrid models that use empirical propagation equations as baseline priors and machine-learning models as correction mechanisms. Such a framework could combine physical interpretability with data-driven adaptability. Finally, the predicted path-loss outputs could be integrated into adaptive network-optimization frameworks, including reinforcement-learning-based power control, handover threshold adaptation, and dynamic cell association.

4. CONCLUSION

This study proposed a Genetic Algorithm-Optimized Weighted Ensemble Learning framework for urban LTE radio propagation modeling using real drive-test PUCCH path-loss measurements collected along an urban corridor in Palembang, Indonesia, at 1800 MHz and 2100 MHz. The proposed model combined four hyperparameter-optimized base learners, namely Random Forest, XGBoost, MLP, and SVR, through GA-based adaptive weighting using out-of-fold predictions. The results show that GA-Based Weighted Blending achieved the best hold-out performance, with an RMSE of 5.5403 dB, MAE of 3.7150 dB, and R^2 of 0.7967. Compared with Average Blending, the proposed model reduced RMSE from 5.6577 dB to 5.5403 dB, corresponding to an improvement of approximately 2.08%. Larger RMSE reductions were observed when compared with Random Forest (6.02%), SVR (12.00%), COST-231 Hata (83.26%), SUI (78.82%), and ECC-33 (75.26%). These findings suggest that adaptive data-driven modeling provides improved prediction accuracy compared with uncalibrated empirical formulas for the investigated LTE Bus-Way measurement corridor in Palembang City. .

The optimized GA weights further revealed that MLP and XGBoost contributed most of the predictive information, while Random Forest and SVR had only marginal influence, indicating that the ensemble acted as an adaptive learner-selection mechanism rather than a simple model average. However, the improvement over XGBoost was not statistically significant; therefore, the proposed framework should be interpreted as an adaptive ensemble strategy that effectively combines heterogeneous predictors and achieves the lowest numerical error among the evaluated models, while further validation is required before claiming broader robustness or generalization. Practically, the model can support LTE network planning, coverage estimation, link-budget analysis, and weak-coverage identification. Future studies should validate the framework using spatially independent routes, cross-city datasets, and locally calibrated empirical baselines, while incorporating explainable artificial intelligence, physics-informed hybrid modeling, and spatio-temporal learning to improve interpretability and generalization.

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