Correlation of Traffic Noise Parameters in Queensland

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ABSTRACT

The current available approaches for predicting a range of road traffic noise level indicators rely solely on Linear Regression models that use either LA10(18H) or LA10(1H) as an input variable. However, a crucial correlation between LA10(18H) and other important indicators is missing from the literature. These indicators are often required to be assessed by regulatory authorities, such as the Queensland Department of Transport and Main Roads. This paper extends the prediction scope of regression models to include important indicators such as LA10(12H), LAeq(15H), LAeq(9H), Max|LA10(1H)|, Max|LAeq(1H)|, and Max|LAmax|. The study also incorporates additional road traffic factors as input variables and compares the performance of several machine learning regression methods. The principal conclusion is that Random Forest consistently yields the lowest prediction error across all indicators, with improvements ranging from 20% to 40% compared to the current Linear Regression approach. Furthermore, averaged indicators perform best when using LA10(18H), annual average daily traffic (AADT), average traffic speed, and the percentage of heavy vehicles as input variables, while maximum-based indicators additionally require the road pavement type. Finally, the R-squared values for the different noise level indicators reach up to 98%, indicating a substantial enhancement in the accuracy of noise level indicator predictions.

1 INTRODUCTION

Environmental noise, particularly from road traffic, poses significant challenges in urban planning and public health due to its negative impact on human well-being (European Commission 2000; Department of Transport and Main Roads 2013). To standardize assessment and regulation, noise is represented through statistical indicators, such as LA10(1H), LA10(12H), LA10(18H), and energy-based indicators, such as LAeq(1H), LAeq(9H), LAeq(15H), that summarize acoustic data meaningfully (Naish, Tan, and Demirbilek 2011). These indicators are used within Australian regulatory frameworks like the Queensland Transport Noise Management Code of Practice and NSW Road Noise Policy (Department of Transport and Main Roads 2013; DECCW 2011). Predictive noise modelling is crucial to assessing potential noise impacts where real-time monitoring is not feasible or possible, such as in early infrastructure planning with traffic forecast data. This data generally includes expected daily average traffic with lack of hourly traffic data which is necessary to predict hourly road traffic noise levels. CoRTN'88, a popular road noise model, generally predicts LA10(18H), using forecasted daily average traffic data. Other sub-18 hour indicators are then derived from the predicted LA10(18H) via Linear Regression (Rajakumara and Mahalinge Gowda 2008; Abbott and Nelson 2002; Naish, Tan, and Demirbilek 2011). However, this approach has limitations: misalignment with required indicators, oversimplified linear assumptions, and underutilization of key traffic variables. To address these issues, this study adopts data science methods capable of learning nonlinear relationships from structured datasets, including hourly noise levels and contextual traffic features like annual average daily traffic, average traffic speed, percentage of heavy vehicles and road pavement type. The aim is to predict six noise indicators, LA10(12H), Max|LA10(1H)|, Max|LAmax|, Max|LAeq(1H)|, LAeq(9H), and LAeq(15H), using advanced regression models. The modelling pipeline includes data cleaning, feature engineering, and model training using methods such as Random Forest, Support Vector Regression, Ridge Regression, Linear Regression, and Multilayer Perceptron (Dasgupta et al. 2011; Huang et al. 2020). Performance is enhanced through hyperparameter tuning with GridSearchCV (Bahmani et al. 2021; Feurer and Hutter 2019) and feature selection via recursive feature elimination (RFE) and permutation importance (Faraway 2021; Altmann et al. 2010; Darst, Malecki, and Engelman 2018). The dataset comprises 69 project directories, each with structured Excel files containing hourly LA10(1H), LAmax, and LAeq(1H), and unstructured PDFs detailing noise monitoring and traffic context. Road traffic noise indicators were computed using aggregation and log-based formulas. Categorical road pavement types were one-hot encoded, excluding Open Graded Asphalt to avoid multicollinearity. By combining traditional noise modelling with data-driven techniques, this research improves prediction accuracy, supports regulatory compliance, and enhances decision-making in environmental noise assessment.

2 METHODS

The aim is to predict six noise indicators, LA10(12H), Max|LA10(1H)|, Max|LAmax|, Max|LAeq(1H)|, LAeq(9H), and LAeq(15H), based on the $L_{A10,18\text{-hour}}$ noise model output, using advanced regression models applied to historical monitoring dataset. The noise monitoring dataset used in this study included a total of 69 locations, generally in the South-East Queensland area, covering a range of road surface types including Dense Graded Asphalt (DGA), Stone Mastic Asphalt (SMA), Bituminous Surface (BS) and Open Graded Asphalt (OGA). The dataset also accounts for variables such as heavy vehicle percentage (HV%) and traffic speed. 2 to 7 days of data was collected per location, with the total dataset covering years from 2011 to 2023. Table 2.1 presents a summary of dataset referred to in the study.

Table 2.1: Summary of Monitoring Dataset

AADT		HV%		Traffic Speed (km/h)		Road Surface	
Value	No. of Datasets	Value	No. of Datasets	Value	No. of Datasets	Value	No. of Datasets
<10k	16	<3%	10	<60	35	DGA	53
10k-20k	22	3-6%	26	60-80	21	SMA	10
20k-40k	20	6-10%	20	81-100	9	BS	4
>40k	11	>10%	13	>100	4	OGA	2
Total	69		69		69		69

Various machine learning regression models, including Random Forest, Support Vector Regression, Ridge Regression, Linear Regression, and Multilayer Perceptron, are evaluated to identify the model with the best predictive performance. This evaluation is conducted separately for each noise indicator: LA10(12H), LAeq(15H), LAeq(9H), Max|LA10(1H)|, Max|LAeq(1H)|, and Max|LAmax|. The method, illustrated in Figure 2.1, begins with importing and tidying the sourced road traffic noise dataset. For each noise indicator, Linear Regression models are first developed using individual features to assess the current modelling approach. To ensure robustness, the evaluation process is repeated ten times, each with a different random seed to vary the data split. In each iteration, the dataset is partitioned into an 80 percent training and validation set and a 20 percent testing set. For each regression model, hyperparameter tuning is performed using cross-validation on the training and validation data to identify the configuration that minimizes mean squared error (MSE). Following this, feature selection is conducted using the optimal hyperparameters, again employing cross-validation to determine the feature subset that yields the lowest mean squared error. Finally, the final model selection is based on performance on the testing dataset. After ten iterations, the results are aggregated to finalize the selection of the best-performing model, hyperparameters, and feature set for each noise indicator.

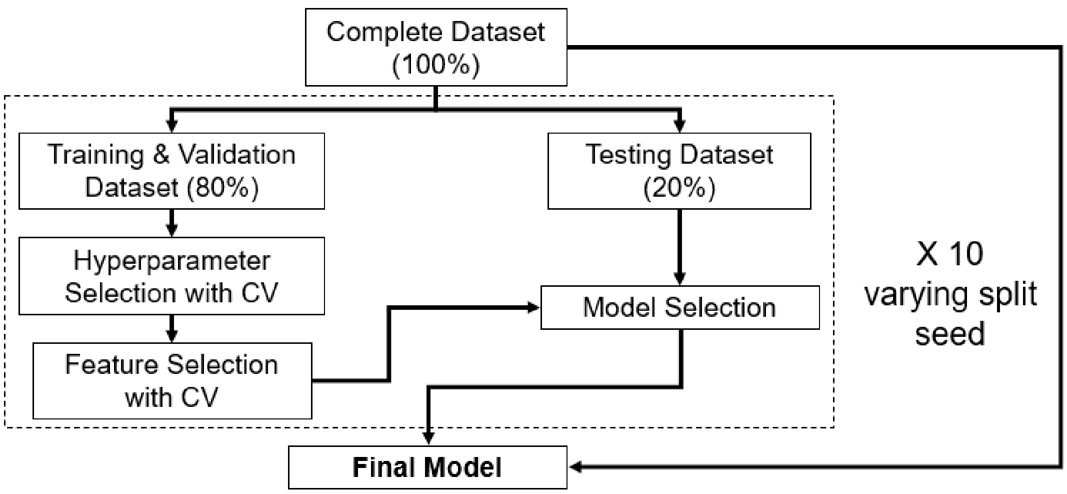


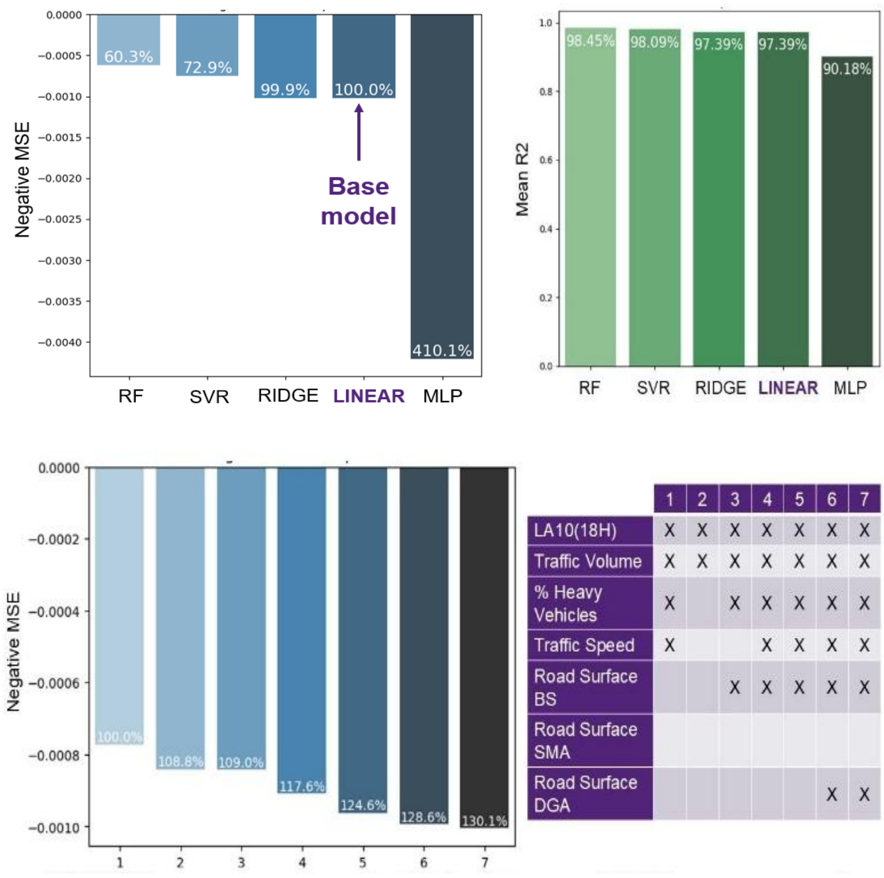
Figure 2.1: Method to evaluate machine learning regression methods

3 RESULT

After applying the method described in Section 2, the results are presented for each noise indicator. It is important to note that the Linear Regression model serves as the baseline, as it reflects the current prediction approach.

3.1 LA10(12H)

Figure 3.1 consolidates the evaluation of five regression models for the noise indicator LA10(12H), highlighting the superior performance of the Random Forest model (RF), which achieves a 39.7% reduction in mean squared error compared to the linear baseline, while Support Vector Regression (SVR) achieves 27.1%. Ridge Regression performs comparably to the base model, whereas the Multilayer Perceptron (MLP) significantly underperforms, increasing the error by a factor of four. All models demonstrate strong explanatory power, with R^2 values exceeding 90%, and Random Forest stands out with an R^2 of 98.45%, confirming its reliability for this indicator. Given its selection, the hyperparameter performance of the Random Forest model was analyzed across 1,440 configurations. Table 3.1 presents the top five hyperparameter sets, all of which yield identical mean squared error values, suggesting they are interchangeable. These configurations consistently use the Friedman MSE criterion, a max depth of unlimited, 30, or 50, max features selected via sqrt or log2, a minimum of one sample per leaf, a minimum split of two samples, and 200 decision trees. Notably, the optimal feature set excludes all road surface variables, which increase mean squared error by at least 18%, indicating their limited relevance. Conversely, excluding the percentage of heavy vehicles or traffic speed reduces performance by approximately 9%, emphasizing their importance. The final model for LA10(12H) is a Random Forest using these hyperparameters and the features LA10(18H), traffic volume, percentage of heavy vehicles, and traffic speed.



	1	2	3	4	5	6	7
LA10(18H)	X	X	X	X	X	X	X
Traffic Volume	X	X	X	X	X	X	X
% Heavy Vehicles	X		X	X	X	X	X
Traffic Speed	X			X	X	X	X
Road Surface BS			X	X	X	X	X
Road Surface SMA							
Road Surface DGA						X	X

Source (Burgos 2024)

Figure 3.1: Regression Models, MSE, R^2, and Feature Set Performance for LA10(12H)

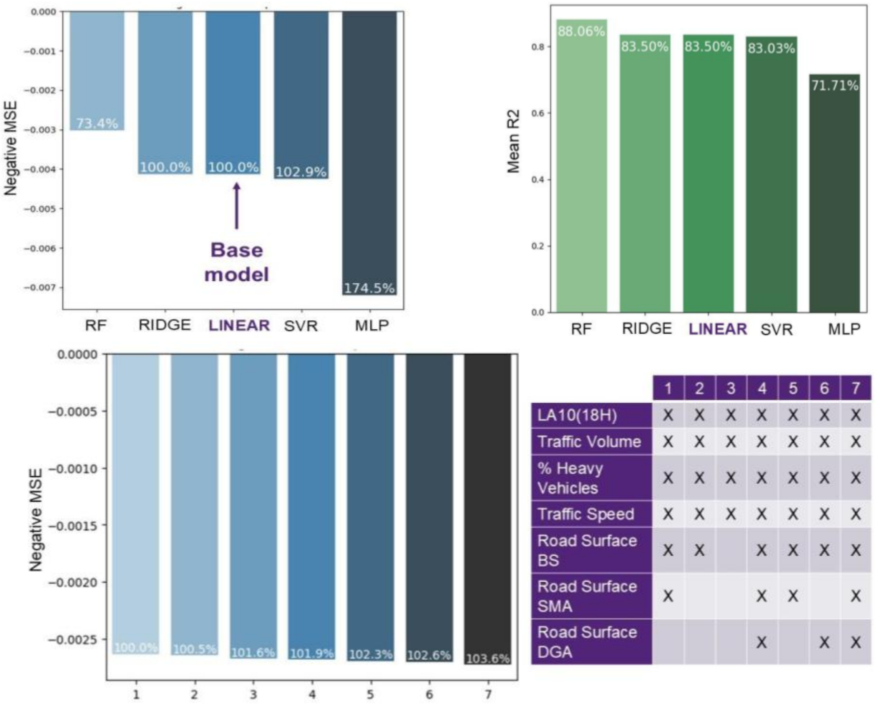
Table 3.1: Best 5 hyperparameters set selection for the noise indicator LA10(12H)

	1	2	3	4	5
Criterion	Friedman	Friedman	Friedman	Friedman	Friedman
Max Depth	unlimited	30	30	50	50
Max Features	sqrt	sqrt	log2	sqrt	log2
Min Samples Leaf	1	1	1	1	1
Min Samples Split	2	2	2	2	2
Number of Estimators	200	200	200	200	200
MSE	0.00107	0.00107	0.00107	0.00107	0.00107

3.2 Max|LA10(1H)|

Figure 3.2 consolidates the evaluation of five regression models for the noise indicator Max|LA10(1H)|, highlighting the superior performance of the Random Forest model, which achieves a 26.6% reduction in mean squared error compared to the linear baseline. Support Vector Regression and Ridge Regression show similar performance to the base model, while the Multilayer Perceptron significantly underperforms, increasing the error by 74.5%. All models, except the Multilayer Perceptron, demonstrate strong explanatory power, with R^2 values exceeding 80%, and Random Forest stands out with an R^2 of 88.06%, confirming its reliability for this indicator. Given its selection, the hyperparameter performance of the Random Forest model was analyzed across 1,440 configurations.

Table 3.2 presents the top five hyperparameter sets, all of which result in the same mean squared error, reinforcing their interchangeability. These configurations consistently apply the Poisson criterion, a max depth of 20 or 30 (including unlimited), max features selected via sqrt or log2, a minimum of one sample per leaf, a minimum split of two samples, and 500 decision trees. Feature performance analysis reveals minimal variation among the top feature sets, with a maximum performance difference of only 3.6%. The selected feature set excludes the road surface DGA and includes LA10(18H), traffic volume, percentage of heavy vehicles, traffic speed, and road surfaces BS and SMA. The final model for Max|LA10(1H)| is a Random Forest using these hyperparameters and the selected features.



Source (Burgos 2024)

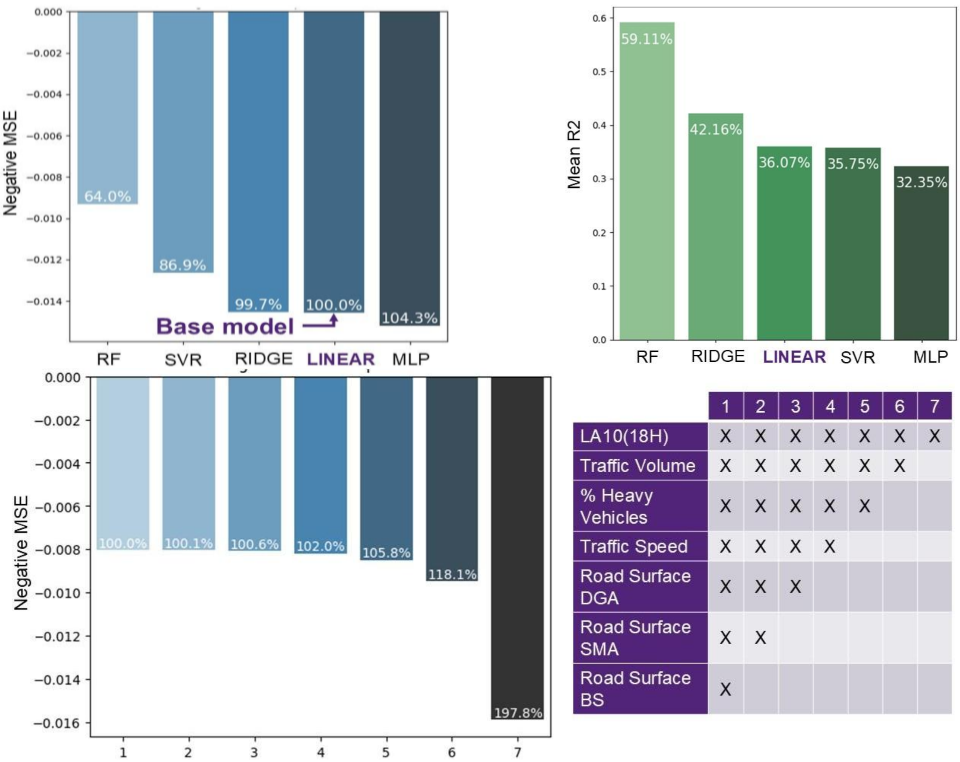
Figure 3.2: Regression Models, MSE, R^2, and Feature Set Performance for Max|LA10(1H)|

Table 3.2: Best 5 hyperparameters set selection for the noise indicator Max|LA10(1H)|

	1	2	3	4	5
Criterion	Poisson	Poisson	Poisson	Poisson	Poisson
Max Depth	20	20	unlimited	unlimited	30
Max Features	sqrt	log2	sqrt	log2	sqrt
Min Samples Leaf	1	1	1	1	1
Min Samples Split	2	2	2	2	2
Number of Estimators	500	500	500	500	500
MSE	0.00271	0.00271	0.00271	0.00271	0.00271

3.3 Max|LAmax|

Figure 3.3 consolidates the evaluation of five regression models for the noise indicator Max|LAmax|, highlighting the superior performance of the Random Forest model, which achieves a 36.0% reduction in mean squared error compared to the linear baseline, while Support Vector Regression achieves only 13.1%. Ridge Regression performs similarly to the base model, and the Multilayer Perceptron slightly underperforms, increasing the error by 4.3%. All models exhibit limited explanatory power, with R^2 values below 60%, yet Random Forest remains the most reliable, with an R^2 of 59.11%, making it the best option for this indicator. Given its selection, the hyperparameter performance of the Random Forest model was analyzed across 1,440 configurations. Table 3.3 presents the top five hyperparameter sets, all yielding the same mean squared error. These configurations use either the Friedman MSE or Poisson criterion, a max depth of unlimited, 10, or 20, max features selected via sqrt or log2, a minimum of one sample per leaf, a split threshold of two or five samples, and 500 decision trees. Feature analysis highlights that the best feature set includes all road surface types, as removing any of them increases the mean squared error by up to 2%. Moreover, excluding percentage of heavy vehicles or traffic speed reduces performance by approximately 18%, and relying solely on LA10(18H), as done in the current approach, doubles the error. The final model for Max|LAmax| is a Random Forest using these hyperparameters and the features LA10(18H), traffic volume, percentage of heavy vehicles, traffic speed, road surface DGA, road surface SMA, and road surface BS.



Source (Burgos 2024)

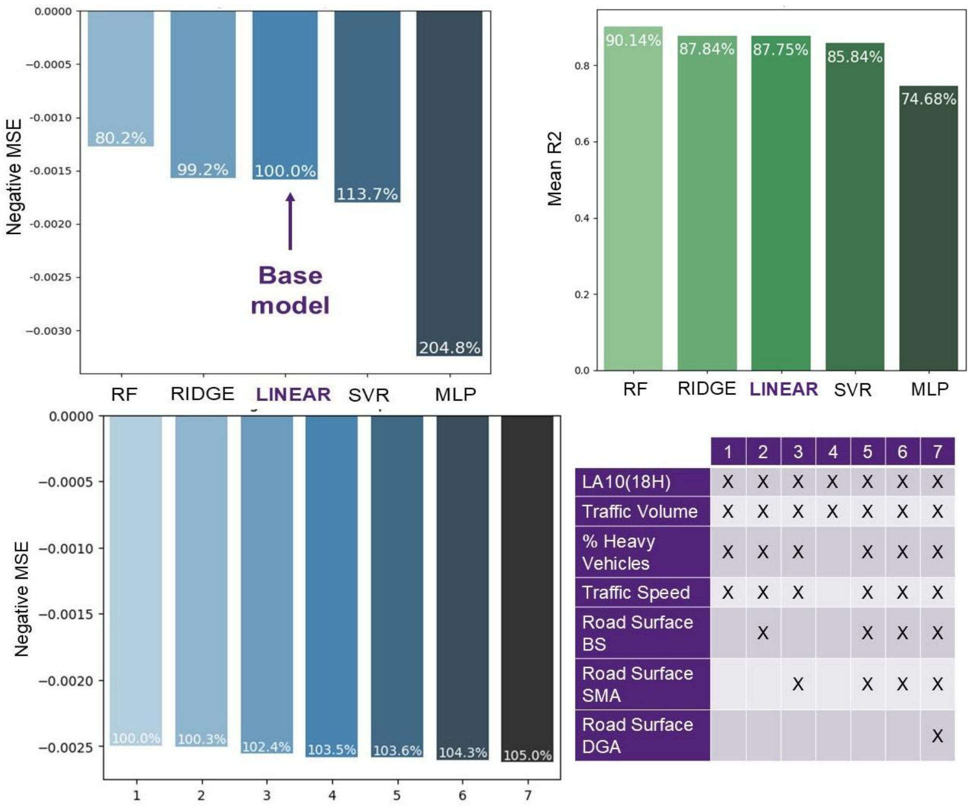
Figure 3.3: Regression Models, MSE, R^2, and Feature Set Performance for Max|LAmax|

Table 3.3: Best 5 hyperparameters set selection for the noise indicator Max|LAmax|

	1	2	3	4	5
Criterion	poisson	poisson	Friedman	Friedman	Friedman
Max Depth	10	10	20	20	Unlimited
Max Features	sqrt	log2	sqrt	log2	sqrt
Min Samples Leaf	1	1	1	1	1
Min Samples Split	2	2	5	5	5
Number of Estimators	500	500	500	500	500
MSE	0.00823	0.00823	0.00823	0.00823	0.00823

3.4 LAeq(9H)

Figure 3.4 consolidates the evaluation of five regression models for the noise indicator LAeq(9H), highlighting the superior performance of the Random Forest model, which achieves a 19.8% reduction in mean squared error compared to the linear baseline. Ridge Regression performs similarly to the base model, while Support Vector Regression increases the error by 13.7%, and the Multilayer Perceptron doubles the mean squared error, indicating significant underperformance. Most models demonstrate strong explanatory power, with R^2 values exceeding 80%, except for the Multilayer Perceptron. Random Forest again stands out with an R^2 of 90.14%, confirming its reliability for this indicator. Given its selection, the hyperparameter performance of the Random Forest model was analyzed across 1,440 configurations. Table 3.4 presents the top five hyperparameter sets, all of which produce identical mean squared error values. These configurations consistently use the Friedman MSE criterion, a max depth of unlimited, 20, or 30, max features selected via sqrt or log2, a minimum of one sample per leaf, a minimum split of two samples, and 200 decision trees. Feature performance analysis shows that the best feature set excludes all road surface variables, and including them increases the mean squared error by up to 5%, suggesting their limited contribution. The final model for LAeq(9H) is a Random Forest using these hyperparameters and the features LA10(18H), traffic volume, percentage of heavy vehicles, and traffic speed.



Source (Burgos 2024)

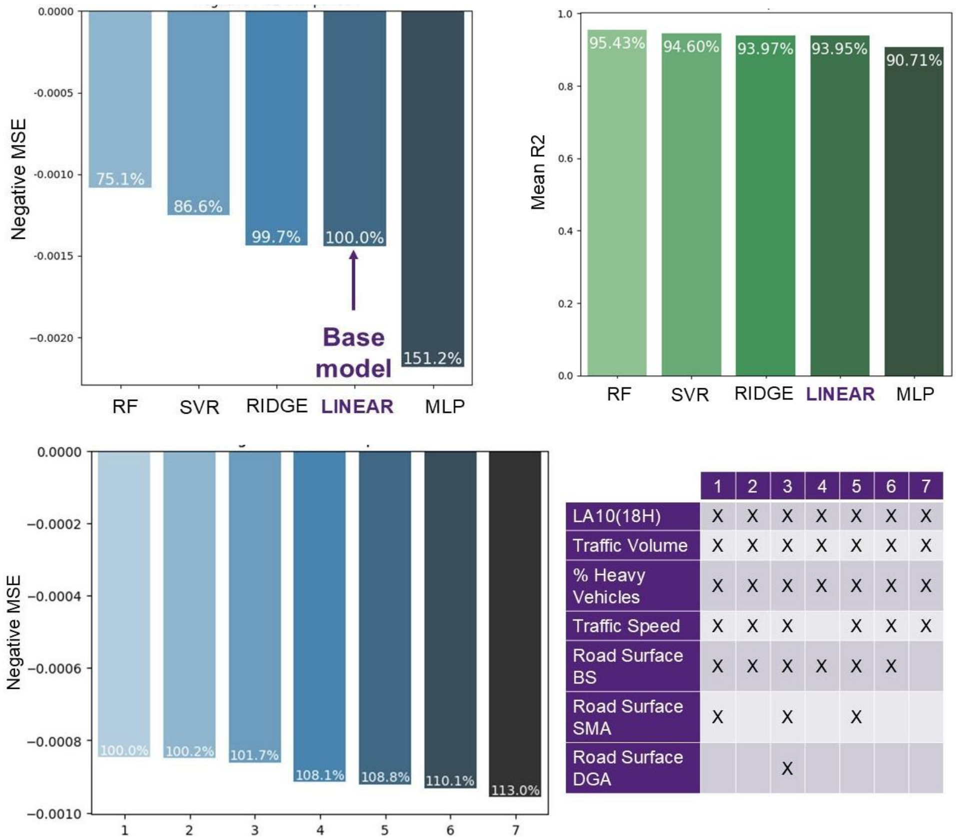
Figure 3.4: Regression Models, MSE, R^2, and Feature Set Performance for LAeq(9H)

Table 3.4: Best 5 hyperparameters set selection for the noise indicator LAeq(9H)

	1	2	3	4	5
Criterion	Friedman	Friedman	Friedman	Friedman	Friedman
Max Depth	20	20	unlimited	unlimited	30
Max Features	sqrt	log2	sqrt	log2	sqrt
Min Samples Leaf	1	1	1	1	1
Min Samples Split	2	2	2	2	2
Number of Estimators	200	200	200	200	200
MSE	0.00264	0.00264	0.00264	0.00264	0.00264

3.5 LAeq(15H)

Figure 3.5 consolidates the evaluation of five regression models for the noise indicator LAeq(15H), highlighting the superior performance of the Random Forest model, which achieves a 24.9% reduction in mean squared error compared to the linear baseline, while Support Vector Regression achieves only 13.4%. Ridge Regression performs similarly to the base model, while the Multilayer Perceptron increases the mean squared error by 51.2%. All models demonstrate strong explanatory power, with R^2 values exceeding 80%, and Random Forest stands out with an R^2 of 95.43%, reinforcing its reliability for this indicator. Given its selection, the hyperparameter performance of the Random Forest model was analyzed across 1,440 configurations. Table 3.5 presents the top five hyperparameter sets, all yielding identical mean squared error values, indicating interchangeability. These sets consistently use the Friedman MSE criterion, with max depths of unlimited, 20, or 30, max features selected via sqrt or log2, a minimum of one sample per leaf, a minimum split of two samples, and 500 decision trees. Feature performance analysis shows that using all features, including some road surface features, yields strong performance, while excluding the road surface features increases the mean squared error by at least 8%. The final model for LAeq(15H) is a Random Forest using these hyperparameters and the features LA10(18H), traffic volume, percentage of heavy vehicles, traffic speed, road surface BS, and road surface SMA.



Source (Burgos 2024)

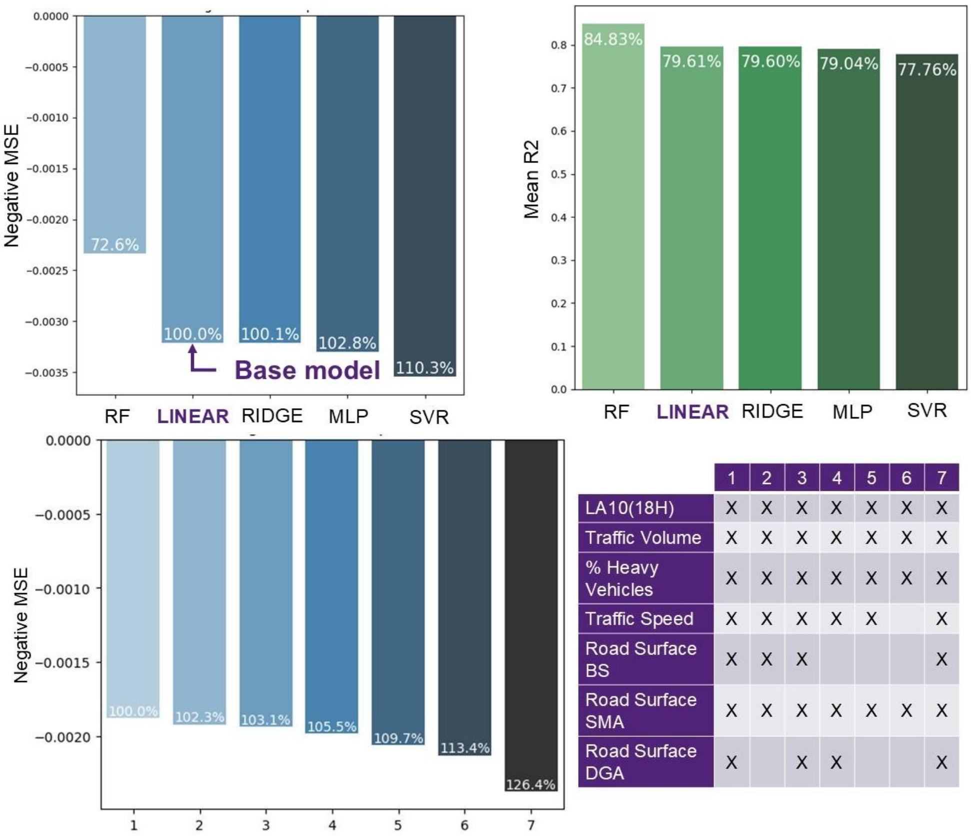
Figure 3.5: Regression Models, MSE, R^2, and Feature Set Performance for LAeq(15H)

Table 3.5: Best 5 hyperparameters set selection for the noise indicator LAeq(15H)

	1	2	3	4	5
Criterion	Friedman	Friedman	Friedman	Friedman	Friedman
Max Depth	20	20	unlimited	unlimited	30
Max Features	sqrt	log2	sqrt	log2	sqrt
Min Samples Leaf	1	1	1	1	1
Min Samples Split	2	2	2	2	2
Number of Estimators	500	500	500	500	500
MSE	0.00095	0.00095	0.00095	0.00095	0.00095

3.6 Max|LAeq(1H)|

Figure 3.6 consolidates the evaluation of five regression models for the noise indicator Max|LAeq(1H)|, highlighting the superior performance of the Random Forest model, which achieves a 27.4% reduction in mean squared error compared to the linear baseline, while Support Vector Regression increases the error by 10.3%. Ridge Regression performs similarly to the base model, and the Multilayer Perceptron increases the mean squared error by 2.8%. Among the five models, only Random Forest demonstrates strong explanatory power, with an R^2 of 84.83%, reinforcing its selection as the most suitable model for this indicator. Given this selection, the hyperparameter performance of the Random Forest model was evaluated across 1,440 configurations. Table 3.6 presents the top five hyperparameter sets, all yielding identical mean squared error values, confirming their interchangeability. These sets use the Poisson criterion, a max depth of unlimited, 30, or 50, max features selected via sqrt or log2, a minimum of one sample per leaf, a minimum split of two samples, and 500 decision trees. Feature analysis shows that the best-performing set includes all available features, and removing any of them reduces performance by at least 2.3%, indicating their collective importance. The final model for Max|LAeq(1H)| is a Random Forest using these hyperparameters and the features LA10(18H), traffic volume, percentage of heavy vehicles, traffic speed, road surface BS, road surface SMA, and road surface DGA.



	1	2	3	4	5	6	7
LA10(18H)	X	X	X	X	X	X	X
Traffic Volume	X	X	X	X	X	X	X
% Heavy Vehicles	X	X	X	X	X	X	X
Traffic Speed	X	X	X	X	X		X
Road Surface BS	X	X	X				X
Road Surface SMA	X	X	X	X	X	X	X
Road Surface DGA	X		X	X			X

Source (Burgos 2024)

Figure 3.6: Regression Models, MSE, R^2, and Feature Set Performance for Max|LAeq(1H)|

Table 3.6: Best 5 hyperparameters set selection for the noise indicator Max|LAeq(1H)|

	1	2	3	4	5
Criterion	poisson	poisson	poisson	poisson	poisson
Max Depth	unlimited	30	30	50	50
Max Features	sqrt	sqrt	log2	sqrt	log2
Min Samples Leaf	1	1	1	1	1
Min Samples Split	2	2	2	2	2
Number of Estimators	500	500	500	500	500
MSE	0.00258	0.00258	0.00258	0.00258	0.00258

4 Noise Indicator Prediction Software

To enable practical application of the selected machine learning models, a user-oriented prediction software was developed. The design focused on promoting understanding, leveraging user input, and encouraging engagement (Dudley and Kristensson 2018). A key feature is the integration of prediction interval error estimation using the Model Agnostic Prediction Interval Estimator (MAPIE) library (Cordier et al. 2023), which supports regression models through various resampling strategies. The Jackknife+ method was considered for its ability to account for variability in the regression function (Barber et al. 2021); however, the Jackknife CV+ method was ultimately implemented to reduce computational costs while still providing reliable prediction intervals(“Theoretical Description Regression : Contents — MAPIE 0.9.1 Documentation” 2022). This setup enables each prediction to include a 95% prediction interval, enhancing transparency and reliability, especially valuable in operational contexts requiring trusted insights. The software encapsulates the optimized model with minimal user input, requiring no data science background. As shown in Figure 4.1, users follow four simple steps: select the noise indicator, input features, submit, and receive the prediction with its 95% confidence bounds.

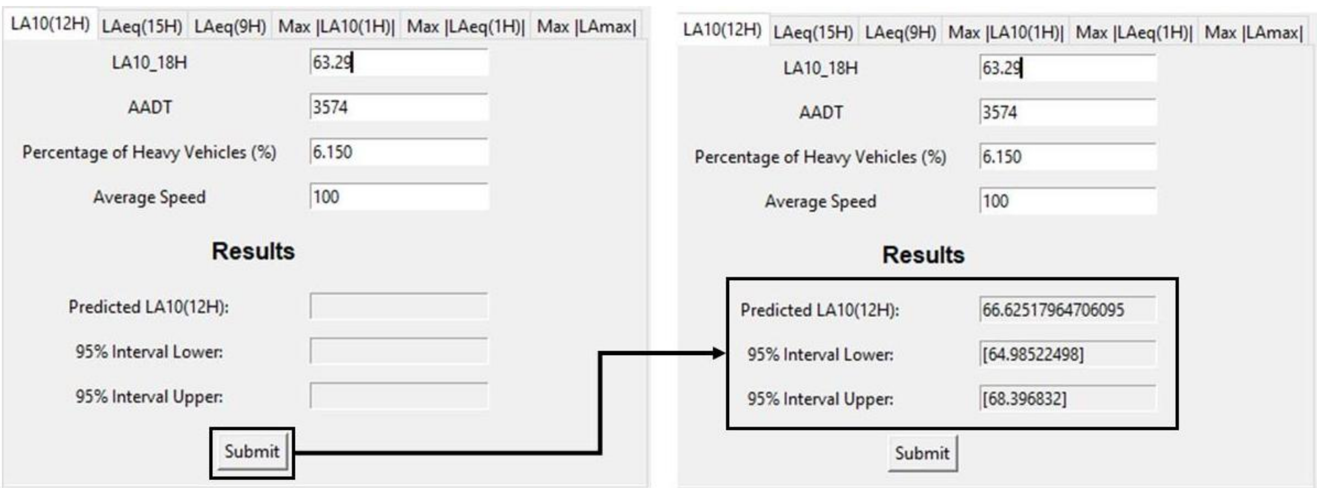


Figure 4.1: Usage of the noise indicator prediction software

5 Conclusion

This work involved the development and evaluation of various regression modelling methods, including hyperparameter tuning and feature selection, with the objective of identifying the most effective model for predicting key noise level indicators. The evaluation demonstrated that the Random Forest model consistently produced the lowest prediction errors across all assessed noise level indicators. For indicators based on averaging, such as LA10(12H), LAeq(9H), and LAeq(15H), the best performance was achieved using features including annual average daily traffic, average traffic speed, and the percentage of heavy vehicles. In contrast, indicators based on maximum values, such as Max|LA10(1H)|, Max|LAeq(1H)|, and Max|Lamax|, required the additional inclusion of road pavement surface as a key predictive feature. Implementation of the Random Forest model resulted in significant reductions in prediction error: approximately 40% for LA10(12H) and Max|LAmax|, 30% for Max|LA10(1H)|, LAeq(15H), and Max|LAeq(1H)|, and 20% for LAeq(9H). In terms of explanatory power, as measured by the R squared metric, the results were 98% for LA10(12H), 95% for LAeq(15H), 90% for Max|LA10(1H)| and LAeq(9H), 85% for Max|LAeq(1H)|, and 60% for Max|LAmax|. These results highlight the effectiveness of the

Random Forest model in accurately predicting road traffic noise indicators and underscore its potential as a reliable tool for supporting data-driven noise assessment. From the authors' perspective, Linear, Ridge and SVR models are not suitable, as the data do not exhibit linear relationships. The performance of MLP could be further improved through additional training. From the acoustic engineering practice, this study, and the software as the final end user-friendly output, enable acoustic engineers and relevant authorities to estimate road traffic noise indicators that cannot be predicted due to lack of hourly traffic data or noise monitoring data. There is also opportunity to incorporate new monitoring data to improve the sample size and cover a wider range of conditions.

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