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EXPLORING THE POTENTIALITIES OF MACHINE LEARNING TECHNIQUES FOR THE ANALYSIS AND THE FORECAST OF ROAD TRAFFIC NOISE LEVELS

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ABSTRACT

Machine Learning (ML) techniques are gaining interest in many scientific applications, including analysing and forecasting road traffic noise. Many alternatives to the classic Road Traffic Noise Models (RTNMs) are then opened: ML provides ways for studying the traffic noise in urban and non-urban environments straightforwardly, using the same input data of the RTNMs. In this work, an analysis of road traffic noise equivalent levels by using ML regressors is described. Those regressors are calibrated on real data (coming from an experimental long-term monitoring station) using the well-known 80%/20% calibration/validation split rule. Splitting of data for calibration and validation is coupled with shuffling of the data themselves to evaluate possible output variations. Even with some differences, regressors exhibit promising potentialities in the simulation of the road traffic noise levels in the case under study. The mean error is very low and comparable with other models available in Literature. The comparison between the distribution of the measured data and the simulated one shows a general good agreement, and also underlines peculiarities of the single regressors.

Keywords: *machine learning, regression analysis, road traffic noise, modelling, computed data.*

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1. INTRODUCTION

Noise has a severe impact on urban environments since it is ubiquitous and its gravity is generally not perceived as other pollutants. People subjected to high noise levels, anyway, experience equal or even worse effects. Consequences of prolonged exposure to high noise levels are numerous: tiredness, lack of sleep, irritability and irascibility, problems in concentration, scarce intelligibility during conversations, tinnitus, and difficulty in conducting daily tasks like study or work [1]. Worse consequences may be related to transient or permanent hearing loss and, even if rarely, to hypertension and/or cardiovascular diseases [2]. Road traffic is responsible for the main part of the impact of noise in a given urban environment, and for this reason, governments are constantly trying to implement noise control and reduction strategies [3]. European Union, for example, aims at a 30% reduction in the number of people subjected to high noise levels before 2030 [4]. Due to this, the importance of monitoring and controlling noise in urban areas is clear, and the implementation of valid measuring strategies is decisive for a successful assessment of the problem. Noise can be directly measured, but when such a direct approach is not possible, modelling is an appropriate alternative. Many models, commonly known as Road Traffic Noise Models (RTNMs), exist since long time, and different RTNMs have been adopted in the past by different national institutions: the CoRTN model, used in the United Kingdom [5], the SonRoad model, used in Switzerland [6]; the NMBP model in France [7]; the ASJ in Japan [8]; the RLS90 in Germany [9] and the Harmonoise model [10]. A comprehensive review of the evolution of RTNMs can be found in [11]. Recently the European Union (EU) has realized and recommended the CNOSSOS-EU model, which is a common procedure for the evaluation and simulation of transportation and industrial noise levels in all European countries [12-13]. CNOSSOS-EU framework is also used for the final development of noise maps. Together with the aforementioned methods, anyway, recently new procedures have recently been investigated and implemented for the assessment of noise. In particular, Machine Learning (ML) techniques have been more and more used for this scope. While RTNMs investigate the direct physical cause-effect relationships between noise emitters characteristics (number of vehicles running, vehicle category, speed) and noise levels at a sensible receiver, ML approaches evaluate such relationship from a statistical point otrof view. In such a way they open to their usability in the same contexts where traditional RTNMs are commonly applied, but also in unusual traffic conditions (presence of roundabouts and/or stops and traffic lights). This is very important considering that RTNMs typically presuppose free-flow conditions. Many examples can be found in the literature. In [14], as an example, Support Vector Machine and Multilinear Regression have been used to evaluate noise in relation to its annoyance to people, generating a final model that correlates noise perception, noise exposure levels, and demographics; in [15] a similar approach is reported, but with more details on the type and number of inputs to be used. An Extreme Gradient Boosting (XGB) approach has been used in [16] to properly relate the performances of the most common traffic noise models and validate them. A wide comparison of the efficiency of several ML approaches can be found in [17]. In the work of Singh et al. [18], a ML approach is used together with a Monte Carlo Simulation for the assessment of noise impact in India. In [19], together with the classic input road traffic parameters, the honking occurrences have been used as input for ML approaches, namely Decision Tree and Random Forest. In [20] the very same regressors have been calibrated by using pass-by noise. All these literature experiences, together with the high potentiality of such approaches, have led the authors to dedicate efforts to the production of a large and comprehensive study on three different ML regressors - Multilinear Regressor (MLR), Decision Tree (DT) and Random Forest (RF) to predict Road traffic noise equivalent levels. After a detailed hyperparameter tuning and calibration approach such models have been validated on a set of road traffic collected data. Specifically, data have been collected by French researchers in a specific extra-urban viaduct in Saint Berthevin, France, during an experimental campaign that lasted several years called "Long Term Monitoring Station" (LTMS). Such data are freely available for research use.

The here presented study stands out for the important aspects of the ML application to road traffic noise simulation. The experimental procedures have been developed using Python programming language. Outputs of the here presented models are provided as hourly continuous equivalent sound level $L_{eq,h}$. The result is a study on the potentiality of the application of such ML approaches on noise assessment and its impact on the environment of urban and extra-urban contexts.

2. MATERIALS AND METHODS

2.1 Workflow of the experimental procedure and used programming environment

Jupyter notebook, a Python environment, has been used to implement the Machine Learning analysis on a DELL personal computer (Intel® Xeon® CPU E3-1245 v5 @3.50 GHz) with 16 GB of RAM installed, 64-bit. The main packages used were: pandas, numpy, scikitlearn, matplotlib and seaborn. The whole experimental procedure consisted of three parts: a first part in which the three chosen regressors have been tuned with the best hyperparameters combination; a second part consisting in the calibration of the regressors, and a final part of validation of the regressor themselves. Figure 1 visually resumes the steps of the process.

2.2 Dataset used for calibration and validation of the regressors

The data used in this experiment to calibrate and validate the regressors come from a large road traffic noise dataset available in the literature, obtained from a large campaign of data collection pursued by the *Unité Mixte de Recherche en Acoustique Environnementale* (UMRAE), within Université Gustave Eiffel, Nantes. In this study, both meteorological and acoustic data were collected by different masts installed in the city of Saint-Berthevin (France) for a period of six years, from 2002 to 2007 [21]. Within this large dataset, the following data were used in this paper: sound equivalent levels, number of light and heavy vehicles, and average speeds for both vehicle categories. Specifically, all the above parameters were recorded in 15-minute intervals, but for this study, they were converted to 60-minute time ranges. To do this, equivalent levels based on 15 minutes were logarithmically summed to calculate the equivalent hourly level. When performing this procedure, authors removed the entries where, for some reasons, equivalent levels were missing. A detailed report of this procedure can be found in [22]. As a result, the dataset used for this contribution was reduced from the original 30347 entries (based on 15 minutes) to a filtered one of 3404 entries (based on 1 hour).

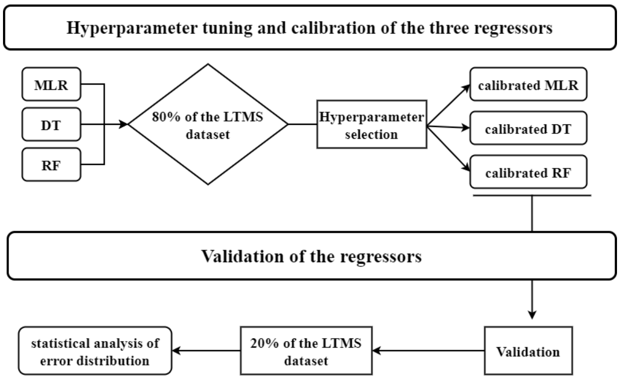

Figure 1: Workflow of the experimental procedure.

2.3 Hyperparameters tuning of the regressors

Hyperparameters tuning is a procedure aiming at finding the best combination possible of the hyperparameters of each regressor to get the best simulation results taking as input a given set of data. In this application, the tuning test has been performed on the same dataset used in the calibration described in subsection 2.4. Different nested cycles have been implemented to check the progressive advances of each test and to save the results. Please note that an in-built function for hyperparameter testing is present in the Scikit-learn package, but the authors preferred to build a personalized one, to have more control over the phases of each iteration. A description of the hyperparameters involved in the tuning procedure is reported below.

For Decision Tree (DT), the hyperparameters are: the criterion to measure the quality of the split, the strategy used to choose the split at each node, the maximum depth of the tree, the minimum number of samples required to split an internal node, the minimum number of samples required to be at a leaf node, the minimum weighted fraction of the sum of weights, the number of features to consider when looking for the best split, the function considering the randomness of the estimator, a maximum number of nodes for each leaf, the value inducing a decrease of the impurity at each node split, the hyperparameter used for Minimal Cost-Complexity Pruning and the monotonicity constraint to enforce on each feature.

For Random Forest (RF), the hyperparameters are: the number of trees in the forest, the function to measure the quality of a split, the maximum depth of the tree, the minimum number of samples required to split an internal node, the minimum number of samples required to be at a leaf node, the minimum weighted fraction of the sum total of weights, the number of features to consider when looking for the best split, a hyperparameter to grow trees with a maximum number of leaves in best-first fashion, the value inducing a decrease of the impurity at each node split, a hyperparameter to establish whether bootstrap samples are used when building trees, a hyperparameter to establish whether to use out-of-bag samples to estimate the generalization score, the number of jobs to run in parallel, a hyperparameter controlling both the randomness of the bootstrapping of the samples used when building trees, the hyperparameter controlling the verbosity when fitting and predicting, a hyperparameter establishing to reuse the solution of the previous call to fit and add more estimators to the ensemble, a complexity hyperparameter used for Minimal Cost-Complexity Pruning, the number of samples to draw to train each base estimator the monotonicity constraint to enforce on each feature.

Finally, for MultiLinear Regressor (MLR), the hyperparameters are: the hyperparameter controlling whether to calculate the intercept or not, the number of jobs to use for the computation, a hyperparameter forcing the coefficients to be all positive.

2.4 Calibration of the regressors

The calibration of the regressors is the process by which every single regressor involved in this experimental study has been trained with a section of the calibration dataset and then has been evaluated in a subsequent validation (test) phase. This process has been carried out following a standard procedure where a section of the data has been devoted to the training of the regressors and the remaining section to their validation. For this specific application 80% of the whole dataset has been used for training, and the remaining 20% for the validation. The train/test split of the dataset is randomly performed by an in-built method of the scikit-learn package that assigns a seed to assure the repeatability of the process. All the analyses reported in Section 3 have been pursued using the same seed, thus fixing the calibration and validation datasets.

2.5 Validation of the regressors

After the calibration of the model, the validation step has been performed by comparing the values simulated by each single regressor with the real one. The validation of the regressors took accounts of statistical analysis of the distribution of the simulated values and of the real ones (mean, standard deviation, skewness, kurtosis) and also a statistical evaluation of the distribution of the errors, where errors have been calculated as the difference of real data and the corresponding simulated ones.

3. RESULTS

3.1 Hyperparameters tuning and calibration results

The first step of evaluation of the work focused on the hyperparameters tuning of the four regressors. As described in subsection 2.3, MLR has been tuned by testing 4 hyperparameters, DT has been tuned by testing 11 hyperparameters and RF has been tuned by testing 17 hyperparameters. In Figure 2 the authors report the boxplots of the distributions of the MAE for the three regressors considered. MLR has a very narrow distribution of MAE values: the minimum value is 1.37 dBA, and the maximum one is 1.39 dBA. DT has a value of MAE ranging from 1.17 dBA to 1.49 dBA. RF has a minimum MAE value of 1.01 dBA and a maximum of 1.32 dBA.

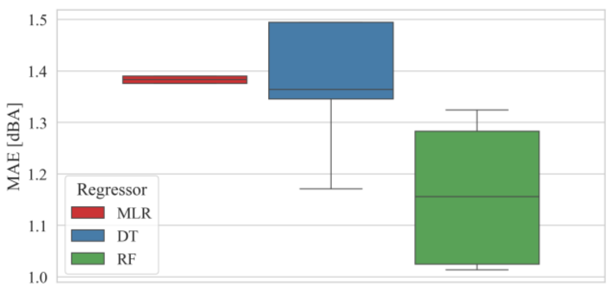

Figure 2: Boxplots of the MAE distributions of all the tested hyperparameters combinations, for all regressors. The solid line is the median of the distribution.

Figure 2 implies an important consideration to be done when calibrating a model since it clarifies how the accuracy of the regressors cannot be considered as a single value coming from a single procedure, but it must be interpreted after taking account of the hyperparameters' tuning. If working on RF, as an example, an output having MAE of 1.3 dBA could be considered as a good value since both MLR and DT have higher average values, but carefully analysing the results of hyperparameters' tuning, it's observed that the final result could be furtherly improved with a better hyperparameters' combination, having an even lower MAE value.
Table 1 reports the best hyperparameters' combination for each regressor as a function of the MAE and mean residuals. The residual is computed as the difference between the measured and the simulated noise levels in the tuning/calibration phase. Consequently, the negative values of the mean residuals found in Table 1 show a slight overestimation of all the models.
Since the tuning has been performed by testing the various hyperparameters' combinations on the same 80% of the overall dataset selected for the calibration, the results of this process provided the final calibration of each regressor.

Table 1: Results of the best hyperparameters' tuning combination for each regressor, in terms of mean error and MAE

Regressor	Mean Error [dBA]	MAE [dBA]
MLR	-0.05	1.38
DT	-0.04	1.17
RF	-0.08	1.01

3.2 Simulation outputs: validation and error analysis

After the regressors tuning and calibration phase, the validation step of the regressors themselves has been made. A due premise to this subsection is that until now authors used the MAE metric as the main indicator for the tuning and calibration phase. The strategy of using MAE as an indicator of the calibration phase has been used to drive the choice of the best hyperparameters setting for each calibration since it is a concise and easy-to-use indicator. In contrast, the validation process has been pursued more in detail, comparing the distributions of real and simulated data, and performing on them statistical investigations. Specifications of such analysis are presented below.
After the hyperparameters selection has been done, the regressors have been fed with input validation data and the final outputs have been collected and compared with the measured levels. Table 2 reports the main statistical descriptors of the measured and simulated equivalent sound level distributions for each regressor, which are plotted in Figure 3.

Table 2. Main statistical descriptors of measured and simulated levels distributions.

	Mean [dBA]	Median [dBA]	St.dev. [dBA]	Skew	Kurt
Measured	72.04	72.52	2.16	-2.13	4.87
MLR	72.09	72.03	0.88	0.49	0.06
DT	72.09	72.41	1.89	-1.50	4.42
RF	72.13	72.38	1.40	-1.79	5.09

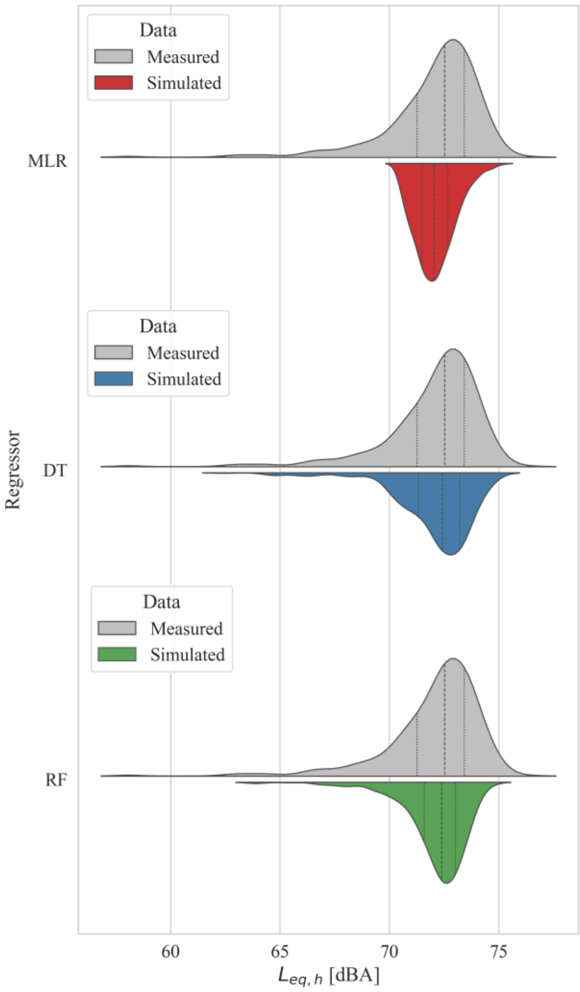

Figure 3. Distributions of measured and simulated equivalent sound levels, calculated by each regressor. The dashed line is the median and the dotted lines are the 1st and 3rd quartile.

At first glance, all the regressors give as output simulated data close to the measured ones, meaning that the hyperparameters' tuning process performed before the calibration indeed selected a good combination for each regressor. Validation data present a mean value of 72.04 dBA, a median of 72.52 dBA, a standard deviation of 2.16 dBA, a skewness of -2.13 (due to the equivalent levels on the left tail of the distribution), and a kurtosis index of 4.87. As for the central tendency metrics, all the regressors perform well, especially with the mean values of the distributions being very close to the measured ones. Median values show a small underestimation of MLR compared to the other regressors.

As for the standard deviations, it is interesting to note how the three regressors' distributions present a value lower than the measured levels one, meaning that no regressor can fully and properly simulate the dispersion of the real data, especially in the tails of the distribution. This behaviour reflects also on the skewness and kurtosis indexes for MLR, which are significantly different from those related to the distribution of the measured levels. More specifically, MLR tends to stabilize around zero skewness and kurtosis indexes. In contrast, DT and RF have higher values (in absolute) for both indexes, close to those of the distribution of the measured levels. MLR, then, can simulate data whose mean value is very close to the real one but misses the shape information of the simulated data distribution. DT and RF also catch the central tendency of the distribution but, in addition, they can also depict the left tail of the distribution, even if not perfectly.

A deeper analysis of the results comes from the investigations of the errors, defined as measured minus simulated equivalent levels in each entry of the dataset (each 1-hour slot), whose distributions are reported in Figure 4. The main statistical descriptors of error distributions for each regressor are resumed in Table 3.

Shapes of the error's distributions are very similar for the three regressors and all have mean values very close to zero (see Table 3). This aspect means that all the chosen regressors can simulate the equivalent noise levels in a good way and that the models aren't affected by any systematic underestimation or overestimation error. From Table 3 it also appears the Gaussian shape of the errors' distribution, since the Shapiro-Wilk index [23], measuring the normality of the distribution, is very high (0.91 for all the regressors).

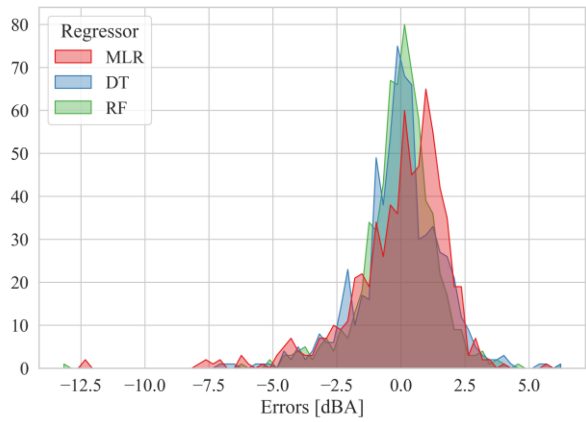

Figure 4. Distributions of the errors according to the regressor used for simulation.

Table 3. Main statistical descriptors of the error distributions for all the regressors.

	MLR	DT	RF
Mean [dBA]	-0.05	-0.04	-0.08
Median[dBA]	0.32	0.02	0.06
St. deviation [dBA]	1.92	1.62	1.48
Kurtosis index	6.32	2.10	10.72
Skewness index	-1.75	-0.42	-1.46
Shapiro-Wilk index	0.89	0.97	0.91
Bowley-Youle index	-0.15	0.00	-0.09

The Bowley-Yule test [24], used to estimate the symmetry of the distributions, is also good since it is very close to zero for all three regressors. Errors of the regressors, then, are peaked to zero and are symmetrically distributed on both negative and positive values, ensuring the stochastic nature of the errors themselves.

A final investigation comes from the visualization of Figure 5, where the scatterplots of measured (on *x*-axis) versus simulated (on *y*-axis) values of $L_{eq,h}$ for all the regressors are reported. The solid red diagonal line represents the ideal 1:1 agreement, whereas the red dashed lines indicate a ±2 dBA deviation, which does not have any statistical validity but it's a commonly accepted range in environmental noise modelling.

As for MLR (top plot), one of the most striking aspects of the model's behaviour is that it does not predict values lower than approximately 70 dBA. The same aspect was observed also in Figure 3, looking at the missing left tail. This result suggests a limitation in its ability to capture the full range of noise levels, possibly due to the linear nature of the model. If the dataset includes lower measured values, the model might be constrained by the way predictor variables interact, leading to an artificial threshold effect. Additionally, the data points are tightly clustered, with a tendency to underestimate higher values, as confirmed by the median simulated level in Table 2 and median error in Table 3, reinforcing the idea that MLR struggles with nonlinear relationships in the data.

The DT model (centre plot) exhibits a much wider scatter, with significant deviation from the 1:1 line. Unlike MLR, it does predict lower values but does so with higher dispersion. The large spread outside the ±2 dBA range reinforces the known tendency of decision trees to create rigid, locally optimized models that may not perform well on new data [25].

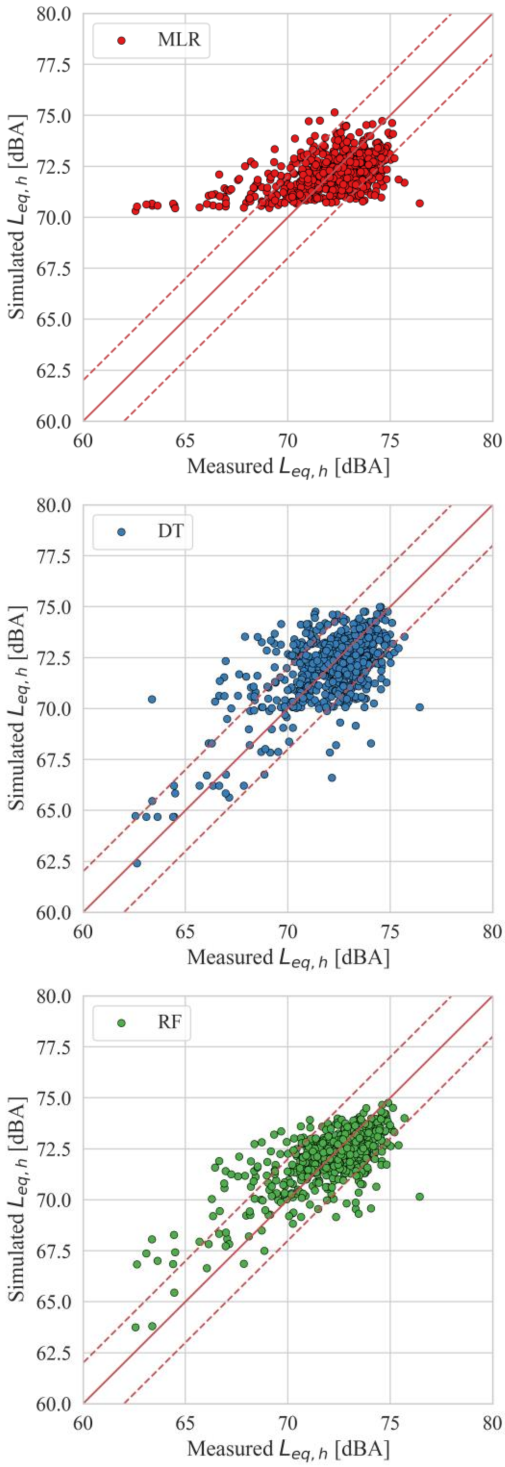

Figure 5. Scatterplots of simulated vs measured data for each regressor

As for the RF model (bottom plot), it provides a more balanced spread of predictions across the range of measured values, without the artificial cut-off seen in MLR. The alignment with the 1:1 line is generally better, although some dispersion is still evident, particularly at the extreme ends of the scale. This suggests that while RF effectively captures nonlinear dependencies, it may still struggle with rare or extreme cases. However, the lower variance compared to DT and the statistics resumed in Table 3 indicate a better ability to generalize.

From a comparative standpoint, the RF model appears to be the most robust, showing good predictive capability across the measured range while maintaining relatively low variability. The MLR model, despite being a simpler approach, fails to predict values below 70 dBA, which raises concerns about its suitability for datasets with a wider dynamic range. Meanwhile, the DT model, though flexible, introduces higher variability.

For a better understanding of such results, the authors calculated the amount of data lying between the ±2 dBA diagonal dashed lines. Table 4 resumes the percentage of data falling within and outside the mentioned interval. RF has the greater amount of data within the ±2 dBA interval, confirming the above comments about its performances.

Table 4. Percentage of data within the ± 2 dB area for each regressor.

	MLR	**DT**	**RF**
Data within ± 2 dBA lines	81.06%	80.91%	87.96%

4. CONCLUSIONS

In this paper three different regressors have been tuned, calibrated and validated on a measured dataset of equivalent continuous sound levels available in literature, to simulate the road traffic noise levels of an extra-urban road. The calibration approach of the regressor is a classical one, where a section of the whole dataset (80%) has been dedicated to the calibration and the remaining part (20%) to the validation of the models. Before the calibration, the regressors were tuned with fine hyperparameter tuning, which revealed the best combination of each regressor to get the lower MAE.

When validating on the dedicated portion of the dataset, outputs show how the simulated values with all regressors fall in a reasonable range of validity. The three regressors seem to get equivalent results when considering central tendency metrics. Anyway, differences exist and can be highlighted by looking at the shape of the distributions of the simulated data, which are slightly different from the measurements' distribution.

MLR is not able to depict the data on the tails, completely missing then noise situations far from the average ones and exhibiting an artificial threshold effect around 70 dBA. For this reason, concerns have been raised regarding its suitability for datasets exhibiting a broader dynamic range, even if the MLR model respects the parsimony principle, with a low number of parameters. DT, while sufficiently accurate, introduces slightly higher variability in the error. The RF model appears to be the most precise, exhibiting good performances in the entire range of measurements and keeping relatively low error mean and dispersion.

In conclusion, machine learning regressors seem to provide a valid option, besides the already existing models, to simulate noise traffic values, starting from the very same input parameters. The future steps of this work will be surely focused on improving the analyses performed on the regressors and including additional models, as well as testing all the regressors on new datasets, possibly related not only to highway road traffic noise data but also urban levels. This will shed light on the usability of such an approach in more complex scenarios, in which several sources may contribute to the environmental noise levels.

5. ACKNOWLEDGMENTS

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