27th International Congress
on Sound and Vibration
The annual congress of
the International Institute
of Acoustics and Vibration (IIAV)
11-16 July, 2021
ICSV27

Annual Congress of the International Institute of Acoustics and Vibration (IIAV)

PREDICTION OF AIRCRAFT NOISE USING MACHINE LEARNING

Miloš Lukić, MSc CE
Faculty of Civil Engineering University of Belgrade, Belgrade, Serbia
e-mail: mlukic@grf.bg.ac.rs
Dejan Gavran, PhD CE
Faculty of Civil Engineering University of Belgrade, Belgrade, Serbia
email: gavran@eunet.rs
Sanja Fric, PhD CE
Faculty of Civil Engineering University of Belgrade, Belgrade, Serbia
email: sfric@grf.bg.ac.rs
Vladan Ilić, PhD CE
Faculty of Civil Engineering University of Belgrade, Belgrade, Serbia
email: vilic@grf.bg.ac.rs
Stefan Vranjevac, MSc CE
Faculty of Civil Engineering University of Belgrade, Belgrade, Serbia
email: svranjevac@grf.bg.ac.rs
Filip Trpčevski, MSc CE
Faculty of Civil Engineering University of Belgrade, Belgrade, Serbia
email: ftrpcevski@grf.bg.ac.rs

In this paper an attempt has been made to predict and evaluate the aircraft-induced noise using model developed by means of machine learning. First step in the development of the model was to artificially calculate noise caused by aircrafts on several locations in vicinity of the airport. To investigate the appropriateness of this approach, the prediction of the developed model was also compared with the most widely used aircraft noise modelling software INM, developed by Federal Aviation Authority. In this research, an artificial neural network was proposed to predict aircraft-produced noise. The precision of the developed model was evaluated using criteria such as the Mean square error (MSE), goodness of fit (R-square) and the Mean absolute error (MAE). Initial idea for developing this model was to propose easy to use noise estimation procedure for airport operators. This procedure would be free of the detailed modelling necessary when using currently available commercial software packages.

Keywords: aircraft, noise, machine learning

1. Introduction

The constant development of society and expanding economy has a direct influence on the increase of transport operations. Aviation industry transport operations have a major influence on cities around the world.

One of the most challenging tasks for the aviation industry is reducing and limiting aircraft noise in the vicinity of airfields. There are many studies [1, 2] that correlate different health issues humans can have if they are subjected to increased noise pollution.Expansion of cities and urbanisation creates number of challenges for airports that are situated in the vicinity of city centres. At those locations, population density is high therefore a large number of people is at risk.

Environmental issues like aviation noise are complex problems dependent on number of variables [3]. Majority of these variables are correlated with the sensitivity of people affected by noise. Crucial ones are the sound level, varying sensitivity of the human ear to different frequencies of sound, the time of day, and the number of occurrences over a period of time. Due to a range of variables that influence aviation noise, several metrics of aircraft noise have been developed over the years.

There are several applicable solutions to the given noise problem, and they are:

- Reduction of noise at source.
- Land-use planning and management
- Noise abatement operational procedures
- Operating Restrictions

To develop applicable noise abatement procedures and analyse operating restrictions airport operators most commonly request detailed noise modelling and prediction studies. Current industry noise models and available software like FAA Integrated Noise Model (INM) [4] or SoundPLAN [5] require trained and experienced users that will calculate noise levels. In this paper, an attempt has been made to develop an easy to use model that airport operators can use during their day to day operations.

To predict road traffic-induced noise, several statistical methods and different models were developed. Artificial neural networks have proven to have better prediction capability than these conventional methods and models [6, 7]. Artificial neural networks are part of a larger field called Machine Learning.

Scope of this paper is developing and testing Machine learning based model for aircraft noise prediction. The main advantages of a Machine Learning based model would be a quick and limited list of input parameters. The model could be used without specialised personnel or engineers, it would be user friendly and significantly faster than conventional noise modelling.

2. Machine learning models

Machine learning is a subset of a broader field called Artificial Intelligence(AI). Machine learning algorithms build a model based on sample data, in order to complete tasks without being explicitly programmed to perform them.

There are three types of machine learning: supervised learning, unsupervised learning, and reinforcement learning. Supervised learning has a goal of developing a model from labelled training data, that allows us to make predictions about unseen or future data. The term "supervised" refers to a set of training examples where the output data is already known.

Regression analysis is type of supervised learning where the prediction of continuous values is the goal.

Figure 1 summarizes a typical supervised learning algorithm, where the training data are passed to a machine learning algorithm for fitting a predictive model that can make predictions on new, unlabelled data inputs.

In this paper, the focus will be on implementing Deep Neural Network algorithm and Random Forest algorithm for regression analysis.

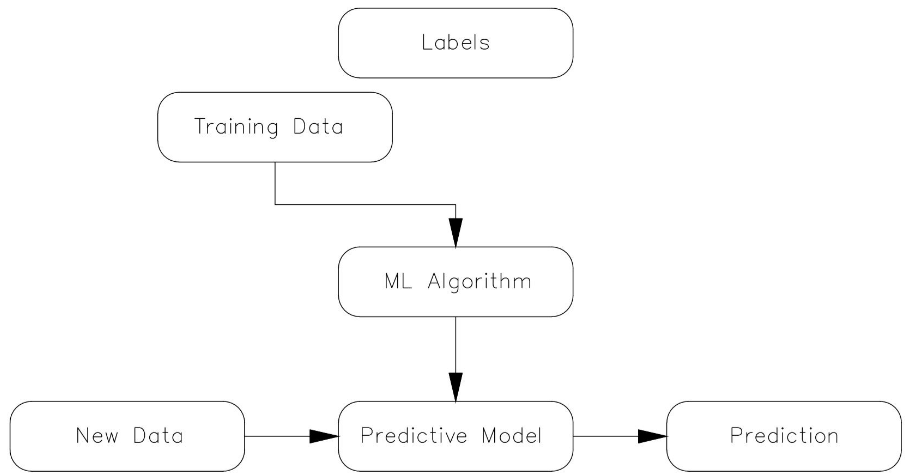

Figure 1: Typical supervised learning workflow.

2.1 Deep Neural Network (DNN)

Deep neural networks [8] can be defined as a subfield of machine learning that deals with efficient training of artificial neural networks (ANN) with many layers. In deep learning, each level learns to transform its input data into a more abstract and composite representation of desired labelled output data.

The learning in deep neural networks occurs by improving the correlation between two neurons when both are active simultaneously during training.

Each neuron has a propagation function that transforms the outputs of the connected neurons. The output of the propagation function goes to an activation function, which switches on when its input exceeds a threshold value.

Deep neural networks have smooth activation functions, such as the logistic function, sigmoid function and the Rectified Linear Unit (ReLU) function.

Figure 2 presents a typical schematic representation of deep neural network and its layer types.

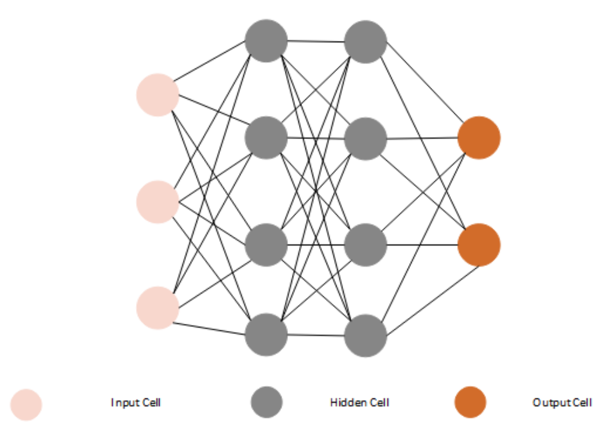

Figure 2: Typical schematic representation of DNN.

2.2 Random Forest (RF)

Different kind of deep learning algorithm besides deep neural networks is the Random Forest[8], or Random Decision Forest. A Random Forest consists of a large number of decision trees. These decision trees can be compared to the neurons of the neural network model. Each decision tree in the random forest model calculates a predicted value based on the same input parameters. The prediction that was calculated by the majority of the trees becomes the model's prediction. The basic concept on which this algorithm relies on is that a vast number of uncorrelated decision trees (models) working as a group will perform better than any of the individual constituent models.

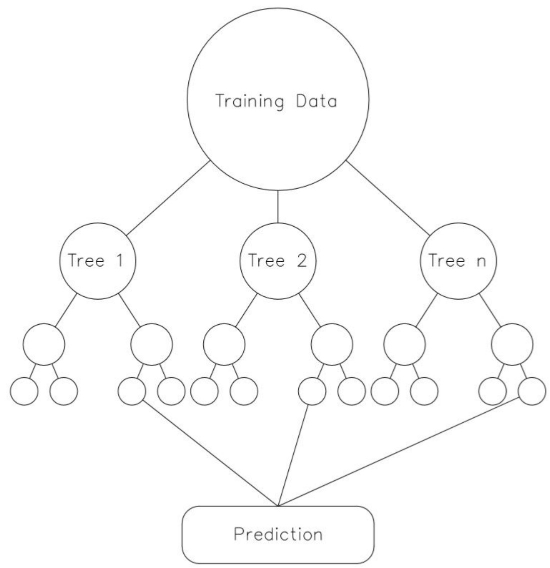

Figure 3: Typical schematic representation of RF.

3. Data set and data preprocessing

The data used in this paper were created in INM software. The starting point for creating data was that we have 4 different types of aircraft that will use an imaginary airport, only take-off operations will be modelled and airport with the surrounding area will be at 0 meters above sea level. Aviation noise is calculated using different metrics. Noise metrics can be defined as measures of noise 'dose'. There are two main types of metrics, single event noise metrics and cumulative noise metrics. In this study single event metric, maximum A-weighted sound level (abbreviation LAMAX), was used [9]. LAMAX is the most commonly used metric for routine noise monitoring at airports. A sound unit for LAMAX metric is called decibel (dB). After defining the input parameters, the noise was calculated at 8200 points in the vicinity of the airport for each type of aircraft. Aircrafts used in this study were selected based on the common aircraft that are operating on international airport Nikola Tesla in Belgrade, Serbia. These aircraft are Airbus A320-200 (code letter C), Boeing B737-300 (code letter C), Embraer EMB145 (code letter C) and Boeing B757-300 (code letter D).

The data were divided into training and testing datasets. Training datasets contain measurements from INM model. In this model, 6560 measurements from several sites were used. Among those, 5248 evaluations were used for the training and validation of the DNN and RF models, whereas 1312 data sets were chosen for testing the model. From 5248 evaluations used for training and validating, 1049 evaluations were used for validation.

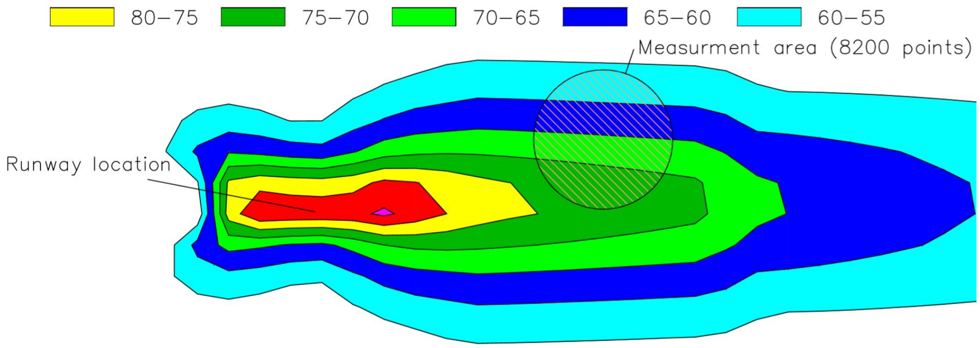

Figure 4: Countour lines of LAMAX metric (dB) from INM software.

The LAMAX metric depends on numerous factors, such as type of airplane, the speed, altitude, distance from observer point (virtual microphone).

The variables in the Machine Learning models are:

- Type of airplane (coded as 1 - A320-200; 2 - B737-300; 3 - B757-300; 4 - EMB145)
- Distance (meters) from the point of virtual microphone on the ground to the aircraft at closest-point-of-approach
- Altitude above airport elevation (meters) of the aircraft at closest-point-of-approach
- Elevation angle (degrees) from the horizontal ground plane to the aircraft at closest-point-of-approach
- True airspeed (m/s) of the aircraft at closest-point-of-approach
- Metric value LAMAX (dB) for a single operation of the given flight

3.1 Data preprocessing

Data set used for the creation of the model was subjected to standard steps for preprocessing data [10]. The first step was data cleaning. Data cleaning consists of filling in missing values, identifying and removing outliers, and deleting duplicates.

Next step was data transformation. Data transformation incluedes normalization and aggregation of data. Normalization of data is applied when input parameters for the model do not have the same scale. For example parameter SPEED (m/s) and ALTITUDE (m).

The final step of data preparation was splitting data into train data and test(validation) data. Figure 5 displays matrix of correlation between 5 input parameters (ACFT ID, DISTANCE, ALTITUDE, ELEV ANG and SPEED) and value of LAMAX that the model needs to predict.

4. Verification of the model for aircraft noise prediction

To test and validate the models, a data set was selected that was not used during the training of the networks. The Machine Learning method, presented in this paper, is an alternative to existing methods for prediction of aircraft noise.

Comparison of measured and predicted LAMAX (dB) values for training data and testing data are shown in Figs 6, 7 and 8, respectively.

The objective function of the Deep Neural Network (DNN) and Random Forest (RF) models was to minimize the mean absolute error (MAE) between the measured and the predicted data. In Machine Learning, MAE is a model evaluation metric often used with regression models. The performance criterion selected for the comparison between the measured and the predicted data is also the mean of squares

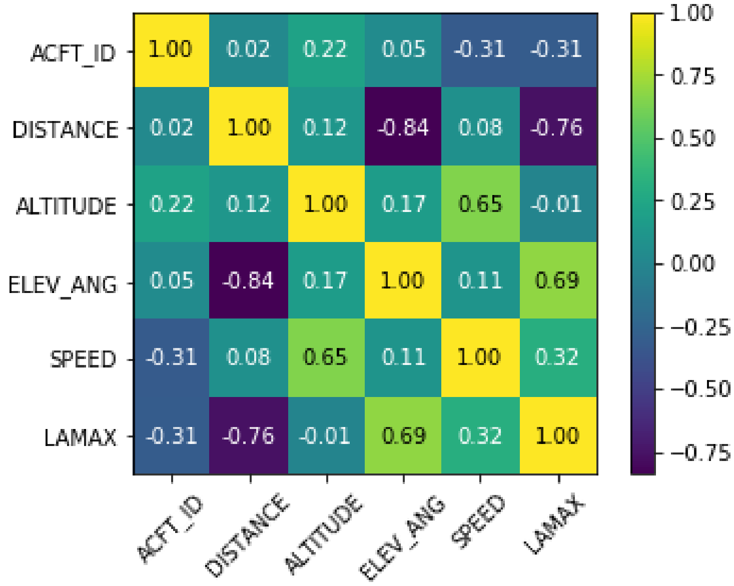

Figure 5: Correlation matrix between data parameters.

due to error (MSE), the standard deviation error and goodness of fit (R-square).

Deep Neural Network model consists of 2 hidden layers with 64 and 128 nodes, respectively. Input layer and hidden layers have ReLU activation function and the output layer has linear activation function. The training of the network was conducted through 15 epochs.

Random Forest model continues the training until reaching 100 decision trees.

It turns out that the Random Forest prediction model outperforms the DNN model . Table 1 shows the comparison of DNN model and the DF model.

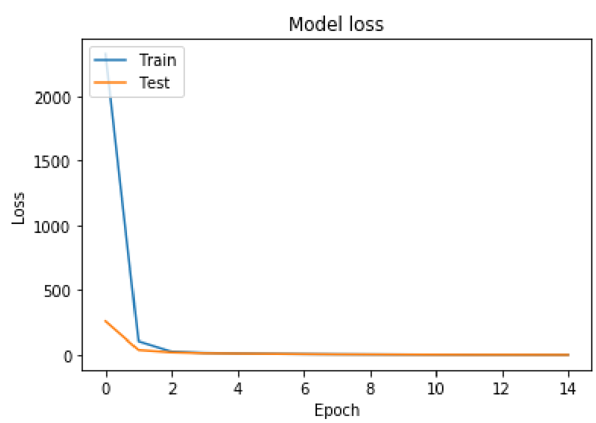

Figure 6: Number of epochs until convergence of the DNN model.

5. Conclusion

A procedure of generating models capable of calculating the maximum A-weighted sound level in the vicinity of the airports was developed and demonstrated in this paper. The method implements machine learning techniques to allow the calculated data in conventional noise calculation software (Integrated

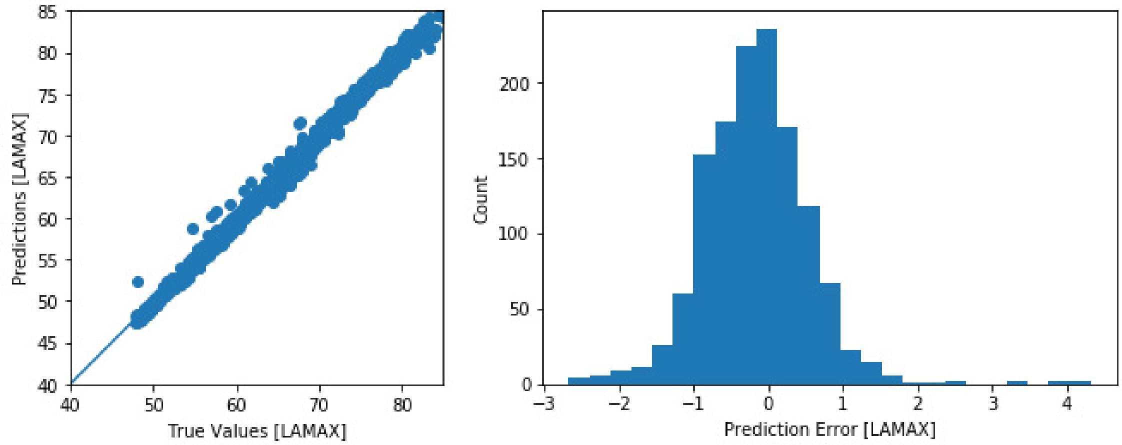

Figure 7: Comparison of measured and predicted LAMAX values for training data in DNN model.

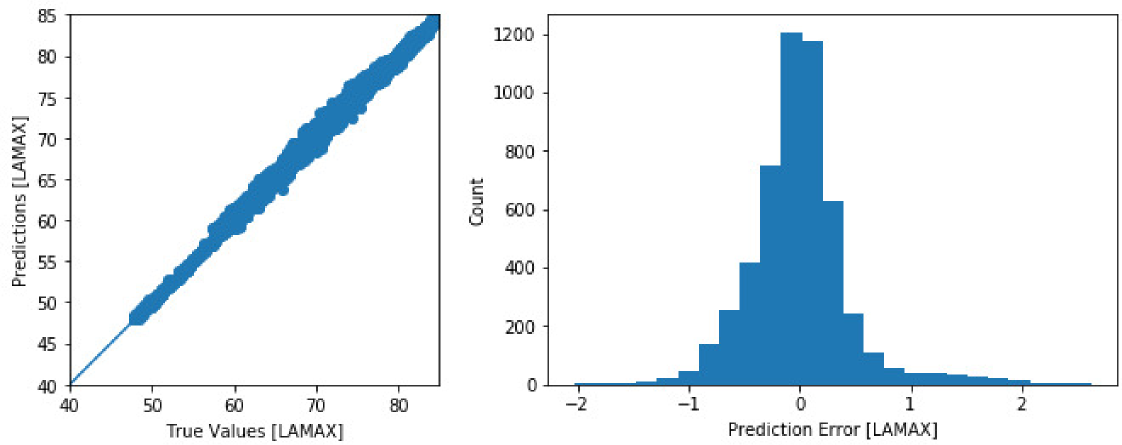

Figure 8: Comparison of measured and predicted LAMAX values for training data in RF model.

Table 1: Comparison of Deep Neural Network and Random Forest models in terms of goodness of fit

Type of Model	R2	MSE	MAE	Error St-dev
DNN (train)	0.9918	1.0390	0.7654	0.7620
Random Forest (train)	0.9971	0.2096	0.3123	0.4579
DNN (test)	0.9926	0.5392	0.5478	0.7163
Random Forest (test)	0.9971	0.2118	0.3059	0.4604

Noise Model) to train a new model. Two different machine learning techniques were assessed. Both Deep Neural Network (DNN) and Random Forest (RF) models were found to achieve good performance.

The mean absolute error of the models is in the range of 0.2 to 0.5 dB. If we know that in this range it is extremely difficult to differentiate these levels, we can with confidence say, that this model has satisfactory accuracy.

It is found that the Random Forest model has better prediction capability than a deep artificial neural network. Random forest model has lower values of the mean of squares due to error (MSE) and mean absolute error (MAE).

One of the main advantages of this model is the prediction speed that is measured in milliseconds after initiating the script with the input parameters. The modelling method developed in this paper is easy to use noise estimation procedure. This procedure is fast and free of the detailed modelling necessary when using currently available commercial software packages, without the sacrifice on the accuracy of predictions.

REFERENCES

1. Franssen, E. A. M., van Wiechen, C. M. A. G., Nagelkerke, N. J. D. and Lebret, E. Aircraft noise around a large international airport and its impact on general health and medication use, *Occupational and Environmental Medicine*, pp. 405–413, (2004).

2. Huss, A., Spoerri, A., Egger, M. and Röösli, M. Aircraft noise, air pollution, and mortality from myocardial infarction, *Epidemiology*, pp. 829–836, (2010).

3. Mahashabde, A., et al. Assessing the environmental impacts of aircraft noise and emissions, *Progress in Aerospace Sciences*, **47** (1), 15 – 52, (2011).

4. He, Dinges, Hemann, Rickel, Mirsky, Roof, Boeker, Gerbi and Senzig, (2007), *Integrated Noise Model (INM) Version 7.0 User's Guide*. ATAC Corporation, DOT/VNTSC, 755 N. Mathilda Ave., Ste 200 Sunnyvale, CA 94085, 1 edn.

5. LLC, S. G. . S. I., (2015), *SoundPLAN User's manual*. SoundPLAN GmbH, Etzwiesenberg 15 71522 Backnang, 1 edn.

6. Nedic, V., Despotovic, D., Cvetanovic, S., Despotovic, M. and Babic, S. Comparison of classical statistical methods and artificial neural network in traffic noise prediction, *Environmental Impact Assessment Review*, pp. 24 – 30, (2014).

7. Hamad, K., Khalil, M. A. and Shanableh, A. Modeling roadway traffic noise in a hot climate using artificial neural networks, *Transportation Research Part D: Transport and Environment*, pp. 161 – 177, (2017).

8. Raschka, S. and Mirjalili, V., *Python Machine Learning: Machine Learning and Deep Learning with Python, Scikit-Learn, and TensorFlow, 2nd Edition*, Packt Publishing, 2 edn. (2017).

9. CONFERENCE, E. C. A., (2016), *ECAC.CEAC Doc 29 Report on Standard Method of Computing Noise Contours around Civil Airports Volume 1: Applications Guide*. EUROPEAN CIVIL AVIATION CONFERENCE, 3 bis, Villa Emile Bergaret 9522 Neuilly-sur-Seine Cédex FRANCE, 4 edn.

10. Ćirković, T., *Smart sale of life insurance implementing data science techniques*, Master of Science Thesis, University of Belgrade, Belgrade, Serbia, (2016).