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An Optimized Deep Neural Network Approach for Vehicular Traffic Noise Trend Modeling

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ABSTRACT Vehicular traffic plays a significant role in terms of economic development; however, it is also a major source of noise pollution. Therefore, it is highly imperative to model traffic noise, especially for expressways due to their high traffic volume and speed, which produce very-high level of traffic noise. Previous traffic prediction models are mostly based on the regression approach and the artificial neural network (ANN), which often fail to describe the trends of noise. In this paper, a deep neural network-based optimization approach is implemented in two ways: i) using different algorithms for training and activation, and ii) integrating with feature selection methods such as correlation-based feature selection (CFS) and wrapper for feature-subset selection (WFS) methods. These methods are integrated to produce traffic noise maps for different time of the day on weekdays, including morning, afternoon, evening, and night. The novelty of this study is the integration of the feature selection method with the deep neural network for vehicular traffic noise modelling. New Klang Valley Expressway (NKVE) in Malaysia was used as a case study due to its increasing heavy and light vehicles, and the motorbike during peak hours, which result in high traffic noise. The results from the models indicate that the WFS-DNN model has the least mean-absolute-deviation (MAD) of 2.28, and the least root-mean-square-error (RMSE) of 3.97. Also, this model shows the best result compared to the other models such as DNN without integration with feature selection methods, CFS-DNN and the ANN networks (MLP and RBF). MAD improvement of 27% - 47% and RMSE improvement of 25% - 38% was achieved compared to other methods. The study provides a generic approach to key parameter selection and dimension reduction with novel trend descriptor which could be useful for future such modelling applications.

INDEX TERMS Vehicular traffic noise modeling, deep neural network, GIS, wrapper for feature-subset selection (WFS), remote sensing.

I. INTRODUCTION

Population growth and increase in economic activities is directly corelated to the increase in traffic around the world. Along with air pollution, noise pollution is considered as one of the major issues in the urban environment. Pinto and Mardones [1] inferred that noise in urban areas is highly associated with peoples' activities, particularly due to transportation and industrial activities. This assertion was further emphasized by the U.S. Department of Transportation (1995) [2], that traffic remains the major source of noise in both rural and urban settlements. It is the most annoying type

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of all noise source found in urban centres [3], [4]. Vehicular noise from expressways is considered as one of the key sources of noise in developed cities due to its high traffic volume, high speed, and different classes of vehicles [5]–[10]. Several studies on traffic noise in urban environment show that the noise has a negative impact on physical and mental health of people including annoyance, anxiety, cardiovascular risks etc. [11]–[16]. Therefore, it is worthy to note that traffic noise is a cause for concern in terms of public health and environment coupled with its nuisance effect [17]. Noise pollution was rated by the World Health Organiza¬tion (WHO) as the third most dangerous pollution after air and water pollution [15]. Therefore, the need to develop traffic noise maps and management plans becomes highly imperative in order to abate the aforementioned effects. So, in line with this perspective, the EU Directive 2002/49/EC (2002) Environmental Noise Directive was issued which recommended that the member states should prepare and publish traffic noise maps and management plans every five years [18]. This plan would enable vehicular traffic noise to be properly evaluated toward a better and sustainable environment.

Determination of noise level is paramount to the successfully implement of any efficient and sustainable noise action plan that minimizes population exposure to noise. Therefore, it is highly imperative to acquire necessary information regarding level of noise to which the public is exposed to [19], [20], [21]. This would enable countries like Malaysia who a working toward improving environmental noise to meet their 2020 master plan [22].

Therefore, this traffic noise model is proposed to evaluate the noise pollution along the New Klang Valley Expressway (NKVE) of Malaysia. This expressway is exposed to a very high traffic noise due to increased heavy and light vehicles, motorbike etc., especially during the peak hours of the weekdays.

II. PREVIOUS WORKS

Various scientific models have been proposed in the past to predict emission of traffic noise using regression techniques [22]–[24]. Even though these models were widely used to identify traffic noise in cities with high accuracy, they are still with some limitations [25], [26]. Since 1950s, several traffic noise predictions (TNP) models and methods have been proposed. [7], [27], [28] carried out a comprehensive and critical review of the most frequently used noise level prediction models. The aforementioned studies reported that the TNP models found in literature commonly applied the linear regression approach, which unfortunately does not consider the intrinsic random characteristics of traffic flow and the way the vehicles run. Only traffic volume is taken into consideration in most of these studies.

Several methods in the past used artificial neural networks (ANN) and genetic algorithms [29], [30]. Cammarata *et al.* [31] first used an ANN model to predict traffic noise level by considering three input parameters: i) vehicle volume estimation was standardized by converting the number of motorcycles, cars, trucks into equivalent number of vehicles, ii) average height of buildings along both sides of the road, and iii) width of the road [32]. The result between the predicted and measured values shows good agreement, with the NN approach yielding better outcome compared with the classical methods. However, the major disadvantage of learning vector quantization (LVQ) neural network approach, as pointed out by the authors, is that its result depends on the training data. This means that network trained for a town layout with a particular road width and building height cannot be used for another city with a different layout [32]. This approach has been further adopted in recent studies [33], [34].

Hamoda [34] predicted the construction noise in the city of Kuwait by applying the neural networks with both the backpropagation and regression analysis. These models were developed based on the phases and equipment types used during construction. The results showed that the general regression network based neural models achieved better accuracy than the backpropagation based networks outcomes. Givargis and Karimi [29] proposed neural, statistical, and mathematical models that predicted the maximum A-weighted noise level (LAmax) for an express train in Tehran-Karaj. A satisfactory result was achieved without any significant differences in the predicted results of the models and the authors suggested that more works are needed to handle sophisticated models.

Genaro *et al.* [35] proposed a model called Multi-layer Perceptron (MLP) to estimate LAeq (Equivalent Continuous Sound Pressure Level) using street level data sourced from Granada, Spain. The neural network results were compared with the results from other mathematical models. Similar numbers of input parameters (25) used in the neural network model were applied to all the other individual mathematical models investigated. It was observed that better predictions were achieved by the MLP model using the neural network compared to the other mathematical models. Also, when the input parameters were reduced to only 11 by applying principal component analysis, a decline in accuracy was observed. However, the predictions using the neural network still outperformed the other mathematical models.

Mansourkhaki *et al.* [36] used ANN-MLP and ANN-RBF to estimate LAeq in parts of Tehran, Iran. The variables used in this study include average speed, traffic volume, and percentage of heavy vehicles. The predicted outcomes were then compared with measures such as the mean-squared-error (MSE) and the coefficient of determination (R2). The ANN-MLP network achieved better performance compared to the ANN-RBF model. Torija and Ruiz [37] applied several machine learning approaches with the addition of feature selection process including the sequential minimal optimisation (SMO), multilayer perceptron (MLP), and the Gaussian processes for regression (GPR) to estimate the sound level. It was observed that the feature-subset selection technique, when used with the SMO or GPR algorithms. According to Azeez *et al.* [38], correlation-based feature selection (CFS) with ANN-MLP showed better performance compared with other methods such as support vector regression (SVR) and liner regression (LR) Models in the prediction of CO emissions from traffic vehicles.

In this study, we develop a novel method for prediction of traffic noise using deep neural network optimisation, where we i) test different algorithms for training and activation, and ii) integrate with feature selection methods such as correlation-based feature selection (CFS) and wrapper for feature-subset selection (WFS) methods. The proposed models are compared with other methods, such as the artificial neural network of the multilayer perceptron (ANN-MLP) and the radial basis function (ANN-RBF) to determine the error (dB) of each model. The performance assessment of the developed models is done based on the mean-absolute-deviation (MAD) and root-mean-square-error (RMSE). The novelty of this study lies in the integration of the feature selection method with the deep neural network, and the output variables of the propped network model that is made in three layers as maximum, minimum and average traffic noise for different time of the day including morning, afternoon, evening, and night. The models were trained and tested with data acquired from the New Klang Valley Expressway (NKVE), Malaysia. Key variables employed in the models are traffic volume, vehicle variety (such as light, heavy vehicles and bus, truck), digital surface elevation (DSM), gradient, density of expressway, temperature, and humidity.

III. STUDY AREA AND DATASET

A. STUDY AREA

The study area is located in Kuala Lumpur, Malaysia as shown in Fig. 1. The NKVE is a heavy traffic route that passes through high-density areas including Kuala Lumpur, Subang, Petaling Jaya, Damansara, Klang and Sungai Buloh. Geographically, it is bounded on longitude 101° 27′ 30″ E to 101° 36′ E and latitude 03° 03′ 30″ N to 03° 07′ N. The NKVE highway is a stretch of about 25 kilometres running from Bukit Raja near Klang town to Jalan Duta, Subang Jaya. The average temperature of the area under consideration is between 80 °F to 83 °F and a wind speed of 5 to 8 mph. The humidity varies between morning and the afternoon, recording an average of 92% - 96% and 66% - 72%, respectively. Recent population indices show that the area harbours over 400,000 people, which is expected to increase by about 0.32% yearly. The area was selected for this research due to its connection to two major settlements - Subang Jaya and Klang regions. It also serves different land uses such as hospital, schools, public service offices, religious infrastructure such as mosques and temples, housing and residential condominium, commercial buildings, and industrial developments.

B. DATASET

In traffic noise calculation and modeling, three basic data types are required [10]. Firstly, traffic flow information such as traffic volume and the proportion of vehicle types that ply the road. These data can be acquired directly in the field using either by manual or automated recording. The second data type is the actual noise coming from the vehicles. These data is usually collected in the field with the aid of noise level meters. The noise data should be collected using suitable devices fitted with advanced filtering technology [23], [24]. This ensures that only vehicular noise is captured, while other types of noise are discarded. There are many types of noise level meters available in the market, such as Sound Level Meter and Datalogger (Class 2) - CENTER323, Digital Sound Level Meter - CEL-240 and others. Finally, the information regarding the road characteristics is important for noise modeling.

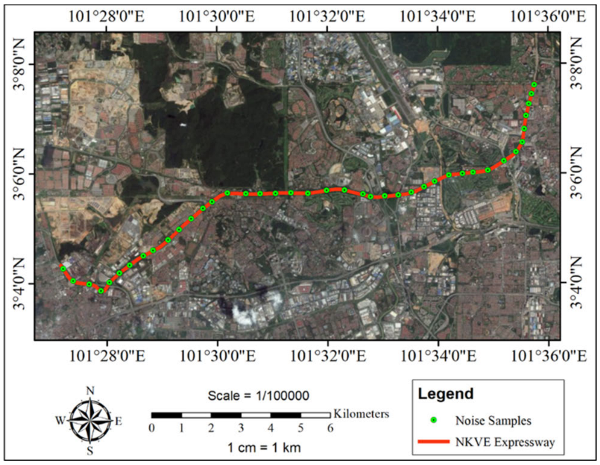

FIGURE 1. The NKVE expressway study area.

In this study, noise levels were measured with Sound Level Meter TES-52 in terms of minimum, maximum, and average values continuously at 15-min intervals using type A filter (dB (A), 0.1dB resolution). The installation of the noise meters was carried out at 10 cm from signs or poles which are separated from noise barriers by at least 2 m allowance. Garmin Global Positioning System (GPS) GPS 60 was used to acquire the geographic coordinates of each sampling location. The noise level measurement was taken four times every day during weekdays. This comprise of morning hours (6.30am-8.30am), afternoon (11.30am-1.30pm), evening (6.30pm – 8.30pm), and night (11pm-12midnight) each day. The traffic volume data were segregated into five classes including light vehicle, heavy vehicle, motorbike, truck, and bus. Meanwhile, the predicted traffic noise maps for the study area are based on GIS modelling. In this study, remote sensing data using light detection and ranging (LiDAR) point clouds, and Worldview-3 images were used (TABLE 1). The LiDAR data were captured by using an airborne system on March 8, 2015. The camera had a spatial resolution of 10 cm, and the laser scanner had a scanning angle of 60° with a camera angle of ±30°. The posting density of the LiDAR data was 3–4 pts/m^2 (average point spacing = 0.41 m). The minimum and maximum elevations

TABLE 1. List of remote sensing data used in this study.

Data	Specification	Acquisition Date
WorldView-3	Eight spectral bands with 1 m spatial resolution, one panchromatic band with a spatial resolution of 0.3 m	April 16, 2015
LiDAR	Spatial resolution of 10 cm, and the laser scanner had a scanning angle of 60° with a camera angle of ±30°	March 8, 2015

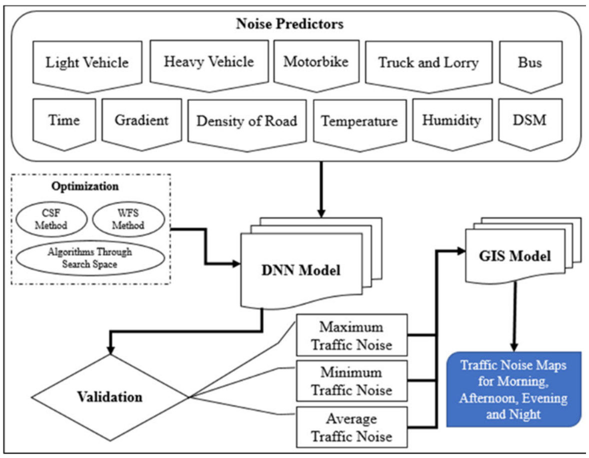

FIGURE 2. The proposed traffic noise model based on the DNN approach.

were 36 and 69 m, respectively. The Worldview-3 image with eight bands of panchromatic spatial resolution, multispectral, short-wave infrared, and Clouds, Aerosols, Vapors, Ice, and Snow (CAVIS) resolution at 0.31, 1.24.

IV. NOISE PREDICTION MODEL

Fig. 2 shows the methodology adopted in this proposed traffic noise model which is based on deep neural network (DNN). The dataset was prepared and managed in GIS database, as well as the predicted traffic noise maps were achieved using GIS. On other hand, optimisation using DNN model was performed using grid search and integration with feature selection methods including correlation-based feature selection (CFS), and wrapper for feature-subset selection (WFS). In order to comprehend the behavior of the proposed DNN model, sensitivity analysis and contribution of various factors were studied. The results of the proposed model were finally validated using data collected from the field. Furthermore, the proposed model was compared with other machine learning models, such as ANN-MLP and ANN-RBF. The comparison of these models is based on performance measures of MAD and RMSE. In addition, we randomly divided the noise data samples into training (70% ≈ 116) and testing (30% ≈ 64) datasets.

A. NOISE PARAMETERS

The main purpose of our model is to estimate the traffic noise level at a particular location and during a specific period of time. In this study, the dependent parameter, that is the highway noise descriptor, is the equivalent continuous noise level per 15 minutes (L_(eq,15)) for the morning, afternoon, evening and night. The noise parameters were pre-determined and selected based on literature review which consider traffic and weather characteristics of the area under consideration. The noise parameters inputted into the model are light vehicle, heavy vehicle, motorbike, truck and lorry, bus, digital surface elevation (DSM), time (i.e. morning, afternoon, evening and night), gradient, density of road, temperature, and humidity. Whilst, the maximum, minimum and average traffic noise are the outputs of the model. Summary statistics of these parameters are shown in TABLE 2.

TABLE 2. Statistical summary of noise predictors.

Parameter	Minimum	Maximum	Mean	Deviation
Maximum Noise	77.10	116.20	106.96	6.86
Minimum Noise	63.40	94.80	80.05	5.98
Average Noise	71.55	113.35	91.52	6.84
Light Vehicle	7.00	2820.00	782.97	719.17
Heavy Vehicle	3.00	618.00	93.22	102.67
Motorbike	2.00	605.00	92.29	115.78
Truck and Lorry	2.00	443.00	63.09	71.18
Bus	1.00	175.00	30.13	31.94
DSM	3.74	41.61	17.27	11.16
Time	Morning, Afternoon, Evening and Night			
Gradient	0.40	203.85	12.81	33.55
Density of Road	0.03	0.05	0.05	0.00
Temperature	19.80	31.60	25.72	3.94
Humidity	42.70	79.60	65.75	9.38

B. DEEP NEURAL NETWORKS

Deep learning exhibits special feature that enable it to reduce local optima problems in non-convex objective function [40]. Three approaches have contributed to the success recorded with deep learning methods which are better learning algorithm, large number of hidden units and better parameter initialization technique [41]. Furthermore, deep architecture seems to be appropriate for higher-level abstractions [42]. Some features of deep learning are helpful across domains which makes it well-suited for transfer learning.

DNN is a machine learning approach that relies on biologically inspired statistical learning models. It is a perception based on a multilayer approach that consists of an interconnection of simple nodes or neurons. It is a nonlinear model represented by inputs and outputs values. The neurons are series of structured nodes systematically connected together form the layers which are randomly connected to the successive layers [43]. DNN is theoretically structured into three layers. The layers are input, hidden, and output layers, which form a complete process sufficient to yield results [43]. The nodes are allocated some numeric weights throughout the input and output processes and are transformed through a simple activation function [44].

The major attraction to the DNN model is the ability of learning. Paul Werbos (1974) developed back propagation and has soon become the commonest learning algorithm employed in ANN. This approach was later rediscovered by researchers (Priddy and Keller, 2005). The DNN algorithm is designed based on error minimization principle through iteration and gradient design as shown in (1). This concept has been successfully used in remote sensing applications. However, their applications are not without challenges, such as high computational complexity coupled with overfitting [45].

$$E = \frac{1}{2}\sum_{i=1}^{L}\left(d_j - o_j^M\right)^2 \tag{1}$$

where, d_j and o_j^M refers to output and current responses at the node "j" of the output layer, respectively, while "L" means the number of nodes found in the output layer. This approach is deployed in an iterative manner in which corrections are made to the parameter weights through computation and addition to the previous outputs as shown in Eqn. 2.

$$\begin{cases} \Delta w_{i,j} = -\mu \dfrac{\partial E}{\partial w_{i,j}} \\ \Delta w_{i,j}(t+1) = \Delta w_{i,j} + \alpha \Delta w_{i,j}(t) \end{cases} \tag{2}$$

where, $w_{i,j}$ is a weight parameter for node i and j, Δ is a positive constant that regulates adjustment to be made refer to as learning rate, α is a momentum factor with values between 0 and 1, while "t" represents the iteration number. Also, α parameter can be referred to as stabilizing or smoothing factor due to its ability to smoothen the changes between the weights [46].

C. OPTIMIZATION PROCEDURE

1) OPTIMIZATION ALGORITHMS THROUGH SEARCH SPACE

The performance of DNN is based on its structure and the hyperparameters used in developing the model. In this research, several hyperparameters are combined and tested to obtain the sub-optimal network model to calculate the vehicular traffic noise. TABLE 3 shows the structure and hyperparameters used to evaluate the model and their domain within the search space.

The former employed the dot product between the inputs and weight parameters with monotonic activation functions, such as sigmoid. In DNN model, it is highly important to employ and very common to use multiple hidden layers. Other network parameters are error function, training algorithm, learning rate, activation function, and momentum. The network complexity is defined by the number of hidden units in the model.

TABLE 3. The hyperparameters used in the proposed model.

Hyperparameter	Search domain
Number of Hidden Units	(10, 5 -50,11)
Training Algorithm	{Gradient descent, Conjugate gradient, Quasi-Newton, Levenberg-Marquardt}
Hidden Activation	{RELU, Logistic, Identity, ELU, SIGMOID}
Output Activation	{RELU, Logistic, Identity, ELU, SIGMOID}
Gradient Momentum	(0.1-0.9) by step of 0.1
Learning Rate	{0.001,0.002, ……, 0.9}

Low prediction may warrant if few hidden units are used due to the deficiency in learning. However, over-fitting of the training data could result when a huge number of hidden units used and could reduce the possibility of generalization of the proposed model. The optimization method is the training algorithm for the calculation of the weights for each individual network node. Many training algorithms exist for DNN that are based on back-propagation including Radial basis function training algorithm (RBFT) and Broyden–Fletcher–Goldfarb–Shanno (BFGS). These algorithms are the most recommended back-propagation approaches used to optimize the DNN architecture [47]. When training networks, optimization score, or an objective function is minimized based on the training dataset, the optimizer usually has gradient momentum parameters and learning rate is given. Furthermore, various activation functions including relu (rectified linear unit), logistic, identity, elu (Exponential Linear Unit), and sigmoid can be applied. The hyperparameters in our models were selected through systematic grid search and executed within the Scikit-Learn environment for 500 epochs. Even though, this approach involves cost of high computation, more realistic results are obtained through systematically tuning of the hyperparameters. Many models were constructed and tested with various combinations of parameters.

2) OPTIMIZATION METHODS FOR FEATURE SELECTION

In this section, two methods of integration with DNN model are explained with correlation-based feature are-subset selection (CFS) and wrapper for feature-subset selection (WFS). Also, the best method of integration with DNN model was selected based on the lower value of *MAD* and *RMSE*.

3) CORRELATION-BASED FEATURE-SUBSET SELECTION (CFS)

One of the most famous methods used for feature selection based on the correlation function is the CFS model. The algorithm is designed based on subgroups selection. It must contain features that strongly correlate to a specific class. This means that all features with low correlation with the class would are neglected. Besides, repeating features are identified due to their exceptional relationship with any one of the other features. The feature will be obliged if its level of prediction within the classes in the territory of the instance space is not as expected by different features. Equation (3) presents the CFS feature subset assessment function.

$$Ms = \frac{k\overline{r_{cf}}}{\sqrt{k + k\,(k-1)\,\overline{r_{ff}}}} \tag{3}$$

where, Ms represent the heuristic "merit" containing k features and feature subset s, $\overline{r_{cf}}$ represents the mean of the feature-class correlation (f 2 s), and $\overline{r_{ff}}$ means the average of the feature-feature inter-correlation.

4) WRAPPER FOR FEATURE-SUBSET SELECTION (WFS)

An induction algorithm, along with a set of training data are presented in the supervised machine learning approach. The induction algorithm acts as a black box while selecting the feature subset in the wrapper approach. The input variables were chosen based on the DNN model. Because its parameters are selected based on each of the regression algorithms. Thereafter, searches were carried out in feature-selection algorithm to find an optimal subset using the induction algorithm itself which is an aspect of the evaluation function. The feature-subset-selection algorithm is considered as a wrapper around the induction algorithm [48]. The WFS approach assesses the attribute sets with the aid of the learning scheme. The procedure requires in the WFS approach are as follows: the induction algorithm is executed on the dataset and divided into internal training and holdout set. However, a different set of features is excluded from the data. The feature subset that has the highest assessment is chosen as the final dataset to be used to run the induction algorithm [48]. Finally, a cross-validation method was used to determine the accuracy of the learning scheme for a set of attributes.

D. THE GIS MODEL

The GIS model was spatially designed as a representation of predicted traffic noise level discharged to atmosphere from highway traffic of the study area. The model was proposed based on the implementation of the final proposed model. The statistical model parameters were converted to a geodatabase by mapping the sample attributes with their corresponding locations obtained via GPS. The model's parameters were transformed to raster format through inverse distance weighting interpolation (IDW) for noise predictor information [48]. IDW technique was selected due to its ability to provide a higher degree of correlation compared with the Kriging and Spline method [49].

On the other hand, a higher distortion was observed in the interpolated results obtained from Kriging and Spline results compared with the IDW values. The model parameters were combined in GIS based on the overlying analysis with the proposed model. This was spatially overlaid on (5∗5) m^2 high-resolution grid, to predict the road traffic noise in the unsampled areas. An overall grid value was calculated using the intersected parameter values which represent the variation and distribution in traffic noise levels in the study area.

E. MODEL EVALUATION

The effectiveness and potential of the developed models were ascertained by calculating Mean-Absolute-Deviation (*MAD)* and Root-Mean-Square-Error (*RMSE)*, in the knowledge that this would give estimates of $L_{eq15\ minutes}$. To evaluate the predictive performance of the models, two performance measures were used. These performance measures indicate the accuracy of predictions of the model by comparing the actual value of the parameters (a_i), predicted value (b_i), number of sample data points (n) and others such as an average of all observed values ($\overline{a}$) and average of all predicted values ($\overline{b}$) which could be useful when comparing different models.

Firstly, the *MAD* was calculated using (4). Determining *MAD* enables researchers to note the relationship between two continuous variables. Next, (5) was used to calculate the *RMSE* for evaluation of the average performance of the model across different test samples.

$$MAD = \frac{\sum_{i=1}^{n} |bi - ai|}{n} \tag{4}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (|bi - ai|)^2}{n}} \tag{5}$$

V. RESULTS AND DISCUSSION

A. THE PROPOSED DEEP NEURAL NETWORK ARCHITECTURE

1) DNN MODEL BASED ON THE OPTIMIZATION ALGORITHMS

Fig. 3 shows our proposed network architecture with about 500 networks training of different combination and parameters. This design is based on the network structure analysis and optimized hyperparameters discussed in Section 4.3.1. The best validation result was obtained with a network of 11 input parameters and two stage 23-7 hidden layers. Also, it shows that the network is best trained with the Levenberg-Marquardt algorithm, while identity algorithm indicated the best output for hidden and output activation layers. Furthermore, the best gradient momentum and learning rates obtained are 0.9 and 0.5, respectively. All the hyperparameters associated with the DNN model were used for the noise prediction while fine-tuning within their search space. The DNN training model achieved 3.4 and 5.2 for *MAD* and *RMSE*, respectively. While, during testing the DNN model achieved 3.61 and 5.57 for *MAD* and *RMSE* of the traffic noise prediction respectively for the study area. The output of the DNN model is defined by maximum, minimum and average equivalent continuous noise level (dB) $L_{eq,15}$. Fig. 4 (a) shows the impact of the number of the hidden units on *MAD* and *RMSE*. Where, we observed that *RMSE* with *MAD* is increasing gradually with an increase in hidden number units.

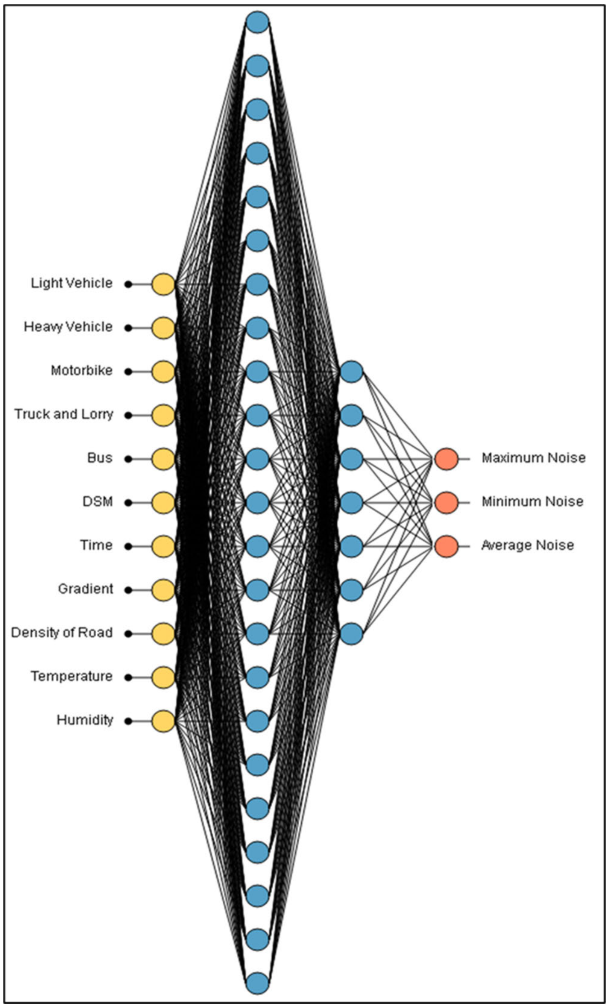

FIGURE 3. DNN architecture for predicting vehicular traffic noise (11-23-17-3).

The DNN model training stage results shown in Fig. 4 (b), where four separate algorithms were tested. The best results were obtained by the Levenberg-Marquardt during the training stage, with 3.4 and 5.2 for *MAD* and *RMSE*, respectively. Likewise, the performance of hidden and output activation methods for the DNN model is shown in Fig. 4 (c) where the best results were obtained by the Identity algorithm with *MAD* of 3.4 and *RMSE* of 5.2.

Regarding the learning rate, the best value was found to be 0.5. The *MAD* and *RMSE* values were significantly decreased at the learning rate between 0.1 – 0.5. On the other hand, it was observed that an increase in momentum of the optimization algorithm improved the *MAD* and *RMSE* of noise prediction. The DNN model has been enhanced from momentum value 0.6 to 0.9. Momentum is vital if local minima stuck is to be avoided. In general, large values of momentum enable fast convergence, while small values cannot always avoid local minima, which slows down training of a system. Fig. 5 shows the best gradient momentum with learning rate of 0.9 and 0.5, respectively with *MAD* of 3.4 and *RMSE* of 5.2.

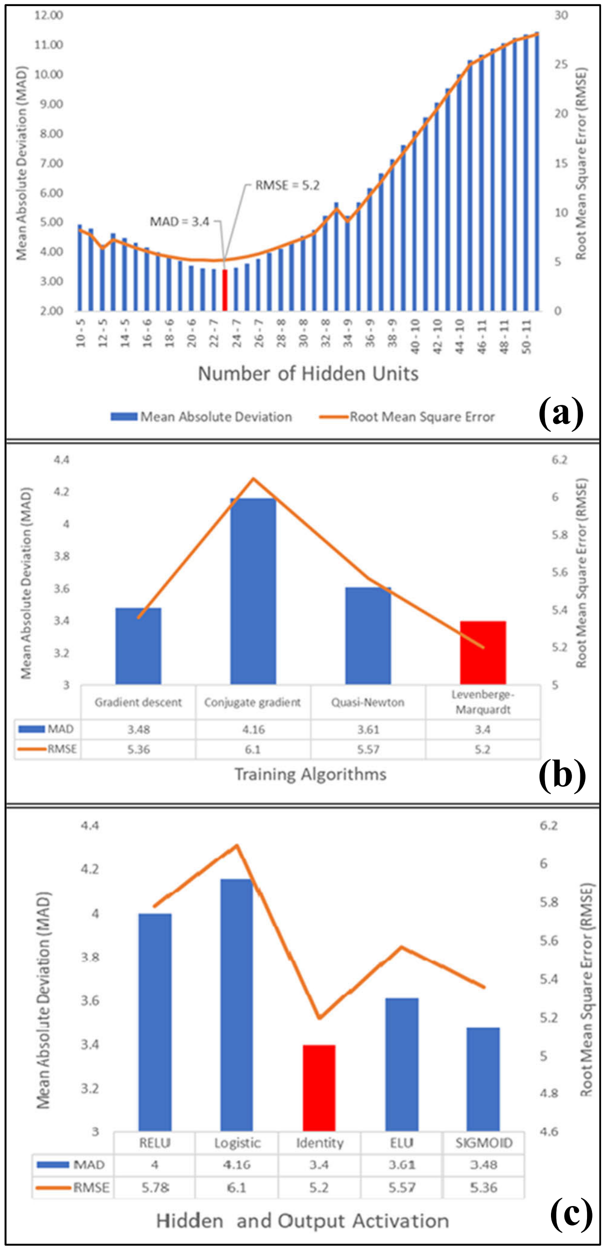

FIGURE 4. (a) The number of hidden units with MAD and RMSE, (b) The training algorithms with MAD and RMSE, and (c) The hidden and output activation with MAD and RMSE.

2) INTEGRATION THE FEATURE SELECTION (CFS AND WFS) WITH DNN MODEL

Based on the results shown in TABLE 4, the noise predictors have different impact levels when used in conjunction with each feature selection method (CFS and WFS) for prediction of the maximum, minimum and average traffic noise level in our selected study area. When the CFS method was used, it was found that the noise predictors such as motorbike, bus and humidity are significant at 100% confidence level, which is imperative to use in the DNN model prediction. In addition, there are other noise predictors that can yield good prediction, such as heavy vehicle, DSM and temperature

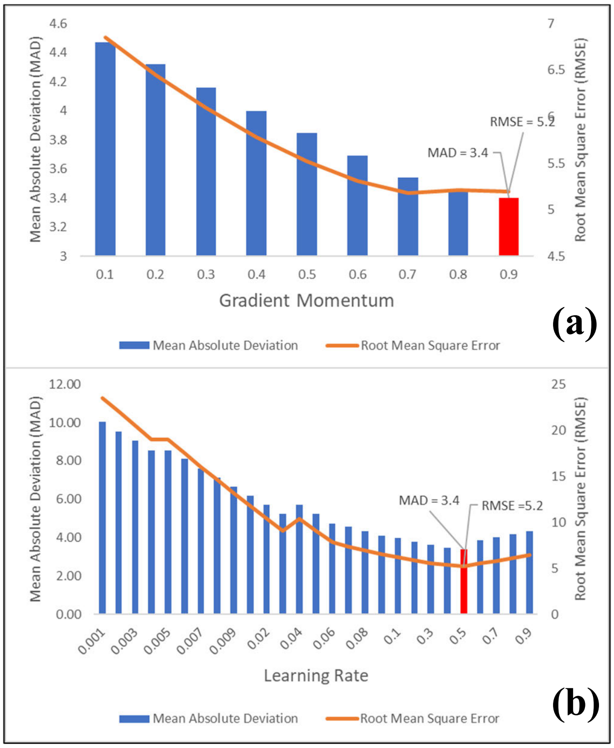

FIGURE 5. **(a) The gradient momentum, and (b) the learning rate with MAD and RMSE.**

parameters. While the noise predictors such as light vehicle, truck and lorry, time, gradient and density of road are not important and used in the model. The CFS method was excluded from the DNN model due to its low correlation with traffic noise predictors, which makes it unsuitable for our DNN prediction model. Based on the WFS method, we found that the noise predictors, such as time and humidity, are significant at 100% confidence level, with substantial use in the DNN model. Also, there are other important parameters used in the DNN model prediction, such as light vehicle, heavy vehicle, motorbike, truck and lorry, bus, DSM and gradient. While, the noise predictors were not significant for DNN prediction model, such as density of road and temperature.

The statistical results indicate that the CFS method was able to establish that the parameters such as light vehicle, truck and lorry, time and gradient are not significant for DNN prediction model. On the other side, the WFS method found those parameters significant, especially the time, truck and lorry parameters for DNN model.

Finally, feature selection methods (CFS and WFS) were integrated with the DNN model and trained. It was found that the training and testing of the WFS-DNN model has the least *MAD* and *RMSE* values. Fig. 6 shows the proposed deep neural network architecture and TABLE 5 describes the hyperparameters of each model which consist of input, number of hidden layer and the output of the model.

TABLE 4. **Results of the contribution of noise predictors using CFS and WFS methods.**

Parameter	CFS method		WFS method	
Maximum Noise	Importance	Used	Importance	Used
Light vehicle	20		70	✓
Heavy vehicle	50	✓	60	✓
Motorbike	100	✓	80	✓
Truck and lorry	40		90	✓
Bus	100	✓	70	✓
DSM	60	✓	70	✓
Time	0		100	✓
Gradient	20		60	✓
Density of road	0		20	
Temperature	80	✓	40	
Humidity	100	✓	100	✓

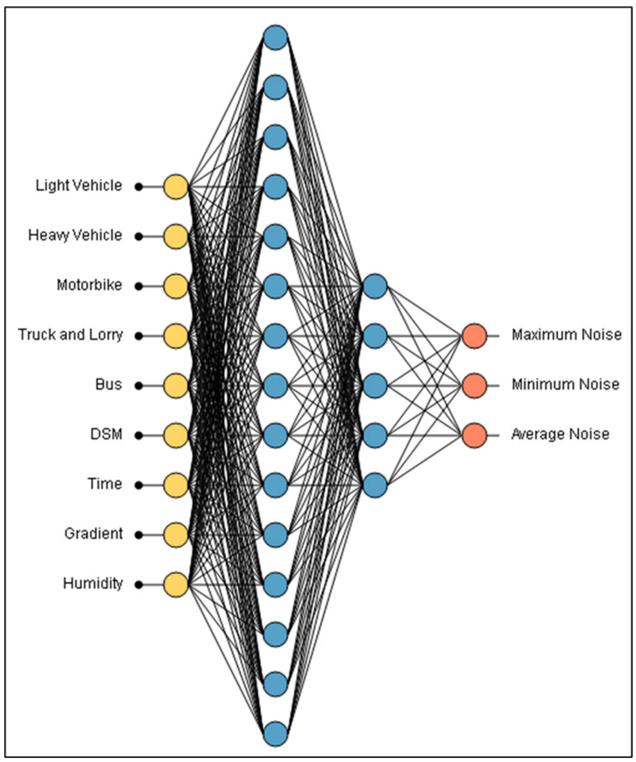

FIGURE 6. **The proposed deep neural network architecture after optimising the input parameters.**

B. COMPARISON WFS-DNN MODEL WITH OTHER MODELS

The proposed model was compared with two ANN variations - ANN-MLP, and ANN-RBF models. The WFS-DNN supersedes the performance of the other models through as shown in TABLE 6. This can be seen in

TABLE 5. Results of DNN, CFS-DNN and WFS-DNN models noise prediction.

Hyperparameter	DNN	CFS-DNN	WFS-DNN
Architecture (input – (number of hidden layer) – output)	11 - (23-7) - 3	6 – (10 – 6) - 3	9 – (15 - 5)- 3
Training model *MAD – RMSE*	3.4 - 5.2	3.05 - 4.27	2.23 – 2.85
Test model (*MAD – RMSE*)	3.29 - 5.56	3.14 – 5.33	2.28- 3.97
Training algorithm	Levenberge-Marquardt		
Hidden and output activation	Identity		
Learning rate	0.5	0.3	
Momentum	0.9		

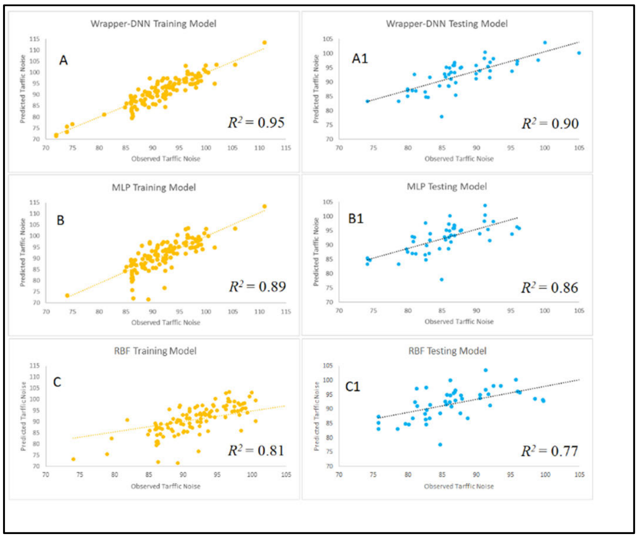

FIGURE 7. **Correlation between observed and predicted vehicular traffic noise using: (A) WFS-DNN training model, (A1) WFS-DNN testing model, (B) ANN-MLP training model, (B1) ANN-MLP testing Model, (C) ANN-RBF training model, and (A1) ANN-RBF testing model.**

both the *MAD* and *RMSE* in both the training and testing results. Also, Fig. 7 shows the correlation between the observed and predicted vehicular traffic noise of WFS-DNN, ANN-MLP and ANN-RBF models during training and testing.

Statistically, the correlation coefficient (R^2) of 0.95 was achieved with *MAD* 2.23 and *RMSE* 2.85 during training. For the testing, R^2 of 0.94, *MAD* is 2.28 and *RMSE* is 3.97 were obtained by the WFS-DNN model. Lower R^2 (0.90, 0.87), *MAD* and *RMSE* are recorded for ANN-RBF for training and testing of the model. However, the ANN-MLP

TABLE 6. Results of WFS-DNN, ANN-MLP and ANN-RBF models noise prediction.

Type of models	Training *MAD*	Testing *MAD*	Training *RMSE*	Testing *RMSE*
WFS-DNN	**2.23**	**2.28**	**2.85**	**3.97**
ANN-MLP	3.69	3.85	5.31	5.52
ANN-RBF	4.16	4.32	6.10	6.45

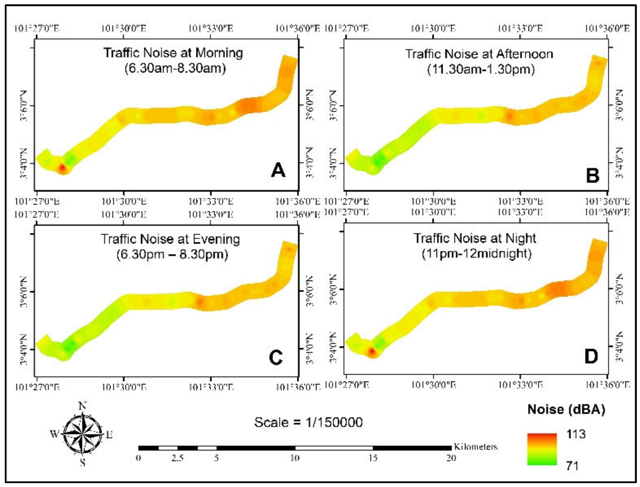

FIGURE 8. **Average traffic noise map at different times of the day: (A) morning (6.30am–8.30am), (B) afternoon (11.30am–1.30pm), (C) evening (6.30pm–8.30pm), and (D) at night (11pm–12 am midnight).**

model shows the best performance compared with ANN-RBF model. Because *MAD* and *RMSE* of the ANN-MLP indicated lower values than the ANN-RBF. Conclusive, it can be inferred that the best model is the WFS-DNN model it has the least *MAD* and *RMSE* of training and testing than the other two models (ANN-MLP and ANN-RBF).

In addition, we found that time and humidity of noise predictors are significant at 100% confidence level, as well as the density of road and temperature. Whereas in the other models, the most important parameters were found to be light vehicle, heavy vehicle, motorbike, truck and lorry, bus, DSM and gradient. Also, results revealed that the density of road and temperature of noise predictors were not significant using the other prediction model.

C. VEHICULAR TRAFFIC NOISE PREDICTION MAPS

Noise distribution maps for the study area were generated using the proposed noise model in GIS. The model produces continuous noise level as the output, accounting for the field conditions and other factors such as topography, weather and other noise predictors. In this research, the noise and traffic volume were measured at different periods, morning, afternoon, evening and night of weekdays. Fig. 8, Fig. 9 and Fig. 10 show the maps of each period. However, this section presents only the recommended maps for planning purposes.

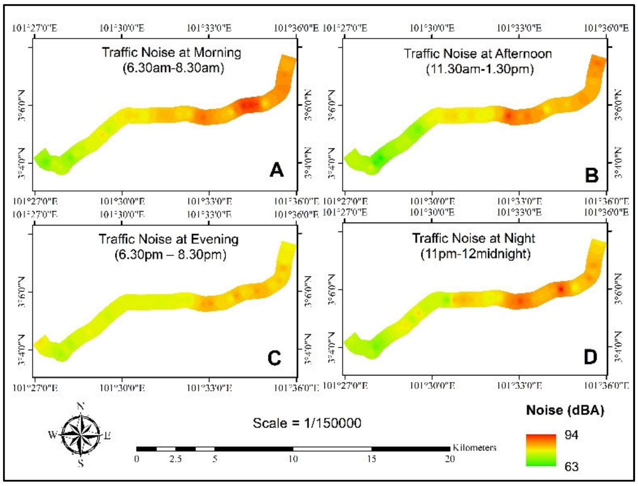

FIGURE 9. The minimum traffic noise map at different times of the day: (A) morning (6.30am–8.30am), (B) afternoon (11.30am–1.30pm), (C) evening (6.30pm–8.30pm), and (D) at night (11pm–12am midnight).

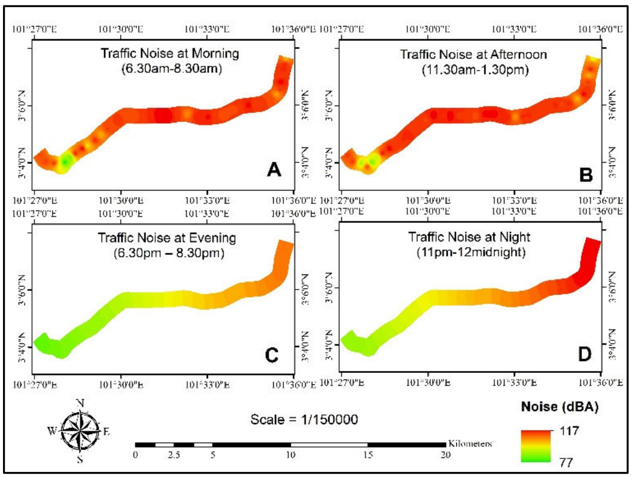

FIGURE 10. The maximum traffic noise map at different times of the day: (A) morning (6.30am–8.30am), (B) afternoon (11.30am–1.30pm), (C) evening (6.30pm–8.30pm), and (D) at night (11pm–12am midnight).

It was discovered that the road is characterized by high traffic noise level in the morning, afternoon and night hours. The following figures show the generated noise distribution maps (maximum, minimum and average traffic noise level) of the study area for a weekday in the morning, afternoon, evening and night.

VI. CONCLUSION

Vehicular emissions such as traffic noise are considered as one key source of environmental pollution affecting urban areas. Plethora of predictive and spatial models have been developed to estimate the impacts of vehicular noise on the environment and public health. In this study, we developed a new DNN based model integrating the feature section methods (CFS and WFS) with GIS mapping. The proposed model accurately predicts the vehicular noise with lowest *MAD* and *RMSE* of 2.23, 2.28 and 2.85, 3.97 for training and testing, respectively. The default model parameters were 11 parameters. After the implementation of the CFS and WFS models, the input parameters were reduced to 6 and 9 parameters each for the CFS-DNN and WSF-DNN models receptively. The WFS-DNN model was observed to be the best model and outperformed the other models such as DNN without integration with feature section methods, CFS-DNN and the ANN based networks (MLP and RBF). Moreover, the model found that the noise predictors such as the time and humidity are significant at 100% confidence level. According to the noise prediction maps, it was observed that the high traffic noise level in the morning, afternoon and night hours. The proposed noise distribution maps were displayed with the maximum, the minimum and the average traffic noise level of the study area for a weekday in the morning, afternoon, evening and night. Although the developed models produced an excellent result, however, it is also important to test the transferability model in different geographical sites to check its efficacy and robustness.

AUTHOR CONTRIBUTIONS

Conceptualization, B.P.; Overall supervision and concept: B.P.; methodology and formal analysis, A.A.; data curation, A.A. and B.P.; Resources, B.P.; writing—original draft preparation, A.A.; writing—review and editing, B.P., S.C., A.A., C.-W.L.; supervision, B.P.; funding – B.P., A.A., C.-W.L, All authors have read and agreed to the published version of the manuscript.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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DATA AVAILABILITY

The data can be made available from the corresponding author.

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