IBRAHIM KHALIL UMAR

ARTIFICIAL INTELLIGENCE BASED MODELS FOR PREDICTION OF VEHICULAR TRAFFIC NOISE

PhD THESIS

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January, 2022

Approval

We certify that we have read the thesis submitted by Ibrahim Khalil UMAR titled **“Artificial Intelligence Based Models for Prediction of Vehicular Traffic Noise**” and that in our combined opinion it is fully adequate, in scope and in quality, as a thesis for the degree of Doctor of Philosophy in Civil Engineering.

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Declaration

I hereby declare that all information, documents, analysis and results in this thesis have been collected and presented according to the academic rules and ethical guidelines of Institute of Graduate Studies, Near East University. I also declare that as required by these rules and conduct, I have fully cited and referenced information and data that are not original to this study.

Ibrahim Khalil Umar

20/01/2022

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Ibrahim Khalil Umar

To my parents

Abstract

Artificial Intelligence Based Models for Prediction of Vehicular Traffic Noise

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Environmental noise and air pollutions induced by vehicular traffic are harmful to human health resulting into many health challenges for urban residents. A reliable and accurate method for the estimation of these pollutants (traffic noise and particulate matter) is therefore essential for creating a healthy environment. In the first stage of the study, three different AI-based models (Ensemble model, hybrid model and emotional neural network (EANN)) were developed for the prediction of vehicular traffic noise using data obtained from twelve different observation points in Nicosia. The most dominant parameters for prediction of vehicular traffic noise in order of their importance were determined to be number of cars, number of van/pickups, and number of trucks, average speed and number of buses. The performance of the developed models was evaluated using the Nash Sutcliffe efficiency (NSE) and the root mean square error (RMSE). The results of all the three proposed models demonstrated higher prediction accuracy than single AI-based models and empirical models. The ensemble modelling was found to have higher the prediction accuracy than the EANN and the hybrid model and could improve the performance of the hybrid and EANN model by up to 4% and 16%, respectively. Lastly, inclusion of traffic noise as an input parameter for the prediction of $Pm_{2.5}$ was found to improve the prediction accuracy by up to 12% in the verification stage hence indicating relevance of traffic noise in modelling $PM_{2.5}$.

***Keywords**:* traffic noise, ensemble modelling, emotional neural network, sensitivity analysis, North Cyprus.

Ozet

Araç Trafik Gürültüsünün Tahmini İçin Yapay Zeka Tabanlı Modeller

Umar, Ibrahim Khalil, Prof. Dr. Hüseyin Gökçekuş, Prof. Dr. Vahid Nourani
Doktora, İnşaat Mühendisliği Bölümü
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Araç trafiğinin neden olduğu çevresel gürültü ve hava kirliliği insan sağlığına zararlıdır ve bu da kent sakinleri için birçok sağlık sorununa yol açar. Bu kirleticilerin (trafik gürültüsü ve partikül madde) tahmini için güvenilir ve doğru bir yöntem bu nedenle sağlıklı bir çevre yaratmak için gereklidir. Çalışmanın ilk aşamasında, Lefkoşa'daki on iki farklı gözlem noktasından elde edilen veriler kullanılarak araç trafik gürültüsünün tahmini için üç farklı AI tabanlı model (Topluluk modeli, hibrit model ve duygusal sinir ağı (EANN)) geliştirilmiştir. Araç trafiği gürültüsünü önem sırasına göre tahmin etmek için en baskın parametreler otomobil sayısı, kamyonet/pikap sayısı ve kamyon sayısı, ortalama hız ve otobüs sayısı olarak belirlendi. Geliştirilen modellerin performansı, Nash Sutcliffe verimliliği (NSE) ve ortalama karekök hatası (RMSE) kullanılarak değerlendirildi. Önerilen üç modelin hepsinin sonuçları, tek AI tabanlı modellerden ve ampirik modellerden daha yüksek tahmin doğruluğu gösterdi. Topluluk modellemenin, EANN ve hibrit modelden daha yüksek tahmin doğruluğuna sahip olduğu ve hibrit ve EANN modelinin performansını sırasıyla %4 ve %16'ya kadar iyileştirebileceği bulundu. Son olarak, trafik gürültüsünün Pm2.5 tahmini için bir girdi parametresi olarak dahil edilmesinin, doğrulama aşamasında tahmin doğruluğunu %12'ye kadar iyileştirdiği ve dolayısıyla PM2.5 modellemesinde trafik gürültüsünün uygunluğunu gösterdiği bulunmuştur.

Anahtar Kelimeler: trafik gürültüsü, topluluk modelleme, duygusal sinir ağı, duyarlılık analizi, Kuzey Kıbrıs.

Table of Content

List of Tables

List of Figures

List of Abbreviations

AI	Artificial Intelligence
AE	ANFIS Ensemble
ANC	Active Noise Control
ANFIS	Adaptive Neuro Fuzzy Inference System
ANN	Artificial Neural Network
ARIMA	Autoregressive Integrated Moving Average
BRT	Boosted Regression Tree
BNN	Boosted Neural Network
BP	Back Propagation
BPNN	Back Propagation Neural Network
BRF	Building Reflective Factor
BSTN	Basic Statistical Traffic Noise model
C	Number of cars
CO	Carbon monoxide
CO_2	Carbon dioxide
CoRTN	Calculation of Road Traffic Noise
CNR	Consiglio Nazionale Delle Ricerche
DC	Determination Coefficient
DNNs	Deep Neural Networks
DSM	Digital Surface Model

DT	Decision Tree
ELM	Extreme Learning Machine
EANN	Emotional Artificial Neural Network
FFNN	Feed Forward Neural Network
FHWA	Federal Highway Administration
FIS	Fuzzy Inference System
GA	Genetic Algorithms
GRNN	Generalized Artificial Neural Network
GEP	Genetic Expression Programming
GIS	Geographic Information System
GPR	Gaussian Process Regression
HV	Heavy Vehicles
IDW	Inverse Distance Weighed Interpolation
$\mathbf{L_{10}}$	10 Percentile Exceeded Sound Level
L-M	Levenberg-Marquardt
$\mathbf{L_{eq}}$	Equivalent Sound Level
LiDAR	Light Detection and Ranging
LSSVR	Least Square Support Vector Regression
LS-DBN	Laplacian Score-Deep Belief Network
LSTM	Long Short-Term Memory
LUR	Land Use Regression
M	Meteorological parameters

M5tree	M5 Model Tree
MARS	Multivariate Adaptive Regression Splines
MAE	Mean Absolute Error
MI	Mutual Information
MLR	Multiple Linear Regression
MSE	Mean Square Error
MV	Medium Vehicles
NSE	Nash Sutcliffe Efficiency
NE	Nonlinear Ensemble (Neural Ensemble)
NN	Neural Network
NO_2	Nitrogen dioxide
NO	Nitrogen oxide
NVG	Number of Vehicles in a Group
ORNAMENT	Ontario Ministry of Transport Traffic Noise Model
OLS	Ordinary Least Squares
P	Percentage of Heavy Vehicles
PBIAS	Percentage Bias
$PM_{2.5}$	Particulate matter 2.5
PM_{10}	Particulate matter 10
Q	Total Traffic Volume
REMELs	Reference Energy Mean Emission Levels

RF	Random Forest
RBF	Radial Basis Function
RJ	Road Junctions
RM	Regression Models
RMSE	Root Mean Square Error
RBFNN	Radial Basis Function Neural Network
RSL	Road Segment Length
SA	Simple Average Ensemble
SLM	Sound Level Meter
SO_2	Sulphur (IV) oxide
SVM	Support Vector Machine
SVR	Support Vector Regression
Tansig	Tangent Sigmoid
V	Average Speed
WA	Weighted Average Ensemble

CHAPTER I

Introduction

Background

Vehicular traffic noise has turn out to be the major source of environmental noise pollution posing serious health problems and lowering the quality of life for people residing in major cities, especially those living along the busy roads of the urban areas (Huang et al. 2017; Wu et al. 2019). Approximately, 65% of people residing in major cities in Europe are exposed to high noise levels, and over 20% are exposed to night-time noise resulting in many health-related problems (Alessandro and Schiavoni 2015). The number of people believed to have been exposed to traffic noise level greater than 55 dB in 2014 is about 125 million, out of which 37 million are exposed to noise level greater than 67 dB (European Environmental Agency, 2014). The effects of sustained exposure to noise is sometimes undermined but researches showed that, it is associated with cognitive performance of school children (Stansfeld and Clark 2015), cardiovascular diseases (Kempen and Babisch 2012), hearing impairment (Tandel and Macwan 2017), annoyance (Méline et al. 2013; Paunović et al. 2014), episodic memory problems (Schlittmeier et al. 2015), sleep disturbance (Ahmadi and Dianat 2019), higher risk of diabetes (Sørensen et al. 2013), and tinnitus (Maschke and Widmann, 2013). Due to the severe implication of the traffic noise on the quality of life and health of people living in urban areas, attempt to understand the complex nature of the traffic noise in order to asses, monitor and model it has become necessary for providing a friendly and healthy environment.

The three components of noise that make up the traffic noise are noise generated as a result of the interaction of the vehicles' tire with road pavement; aerodynamically generated noise due to the airflow turbulent through and around the vehicle; propulsion noise from engine, exhaust and transmission. Aerodynamically generated noise dominates other forms of the traffic noise in high-speed roads while the tire pavement interaction is the dominant on low-speed roads (Sandberg and Ejsmont, 2002). For analysis and management of noise pollution, noise maps are usually developed for presentation of acoustic situation of an area. These maps usually help the stakeholders to easily visualize the exposure level and apply appropriate mitigation measures. The traditional way of reducing exposure to vehicular traffic noise is the construction of noise barriers along the propagation path, because these barriers are usually hermetic and dense enough to screen noise from the source to the receiver (Fredianelli et al., 2019b). But, recent studies have focused on finding innovative and possibly "green" solutions for the traffic noise pollution such as live and integrated noise monitoring systems (Wong et al. 2018). Other sustainable mitigation measures include the use of sustainable metamaterial absorber (Danihelová et al. 2019), application of sonic crystals noise barriers made of recycled materials (Fredianelli et al., 2019b), use of electric car and car sharing hence reducing the overall traffic volume on the roads (Kim et al. 2015), and use of low emission surfaces in construction (Licitra et al. 2015).

Traffic noise are usually measured physically in the field or using verified estimation models. The physical measurements are costly, dangerous, time consuming and sometimes infeasible for large metropolitan areas. Based on this reason, as early as 1950s, researchers have been developing mathematical models for estimation of level of vehicular traffic noise because mathematical models provide faster and cost-effective means of measuring traffic noise than the physical measurements (Ali Khalil et al. 2019). Some of the most common empirical models for the prediction of vehicular traffic noise include the Nord 2000 model, federal highway administration (FHWA) model, German RLS 90 model, Calculation of road traffic noise (CoRTN) model, ASJ RTN-model 2008, NMPB-Routes-2008 model, Harmonoise model, Son Road model, and CNOSSOS-EU model which have been critically reviewed by Garg and Maji (2014). The inputs used in most of these models are traffic characteristics irrespective of the country or region. Real time monitoring of noise pollution using wireless sensors has provided a satisfactory result (σ_{max} =2.1dBA) in a study conducted in Milan (Zambon et al., 2017, 2018). The empirical noise models for the prediction of traffic noise are believed to be reliable in predicting the traffic noise of the country they are designed for, but cannot perform well in places with significant variation in the traffic composition (Federal Highway Administration 2016).

In addition to the non-generalization problem of the classical models due to the differences in local conditions such as road geometry, traffic volume and composition, the use of the classical models requires an in-depth understanding of the physical process and interaction between the traffic noise and the noise generators. The empirical models also proved to provide lower prediction accuracy than AI-based models in the prediction of nonlinear processes. The limitations of the classical models give rise to the application of several machine learning algorithms such as genetic algorithm (GA), artificial neural network (ANN), random forest (RF), support vector machine (SVM), adaptive neuro fuzzy inference system (ANFIS) and decision trees (DT) models for the prediction of roadway traffic noise, due to their accuracy and robustness in handling nonlinear processes like the traffic noise. For examples, Nedic et al., (2014) compared the performance of an ANN model with some statistical models for the estimation of highway traffic noise and the results affirmed the superiority of the ANN over other applied models. Kumar et al., (2014) employed ANN for modelling the roadway traffic noise of Punjab, India using the average speed, hourly traffic volume and heavy vehicle percentage as the model's inputs. Research conducted in Patiala, India evaluated and compared the performance of DT, RF, ANN and generalized linear model for roadway traffic noise estimation. The result showed that RF is more accurate and stable in the traffic noise prediction (Singh et al., 2016). Bravo-Moncayo et al., (2019) utilized three different machine learning approaches (ANN, SVM and multi-linear regression (MLR)) for the assessment of roadway traffic noise annoyance. The result obtained with the ANN model demonstrated higher accuracy than the other three models. Compared to the MLR and the SVM model, the modelling error in training phase was reduced by 42% and 35%, respectively and in testing stage the error was reduced by 24% for MLR and 19% for SVM model. Traffic noise in the hot climate of Sharjah, Dubai was modelled by ANN using five input variables namely mean speed, volume of heavy and light vehicles, road temperature and distance from the pavement edge. Comparing the efficiency of the developed ANN model with Basic Statistical Traffic Noise model (BSTN) and Ontario ministry of transport traffic noise model (ORNAMENT) in the prediction of roadway traffic noise proved superiority of the ANN model over the empirical models (Hamad et al. 2017). ANFIS model was also found to have higher prediction accuracy than FHWA, CRTN and RM models in a study performed by Sharma et al., (2018). ANN model has demonstrated superiority over two conventional roadway noise models (RLS90 and Criterion model) in the estimation of roadway noise in the mountainous city of Chongqing, China. The ANN had the least error of 1.60 dBA, while the RLS90 and Criterion had a forecasted error of 4.54 dBA and 6.70 dBA, respectively. The models input variables were traffic volume, speed, heavy-vehicle and road gradient (Chen et al. 2020a). Ahmed and Pradhan (2019) developed an ANN model for both prediction and model the promulgation of roadway noise emanation in a new expressway in Shah Alam, Malaysia. The model was found to have accuracy of 78.4% and an error of less than 4.02 dBA. Recently, Nourani et al., (2020a) developed a traffic noise model using an ensemble model that combines the outputs of AI-based models and a linear model where, the result of the ensemble approach provided higher accuracy than the single models. An emotional neural network (ENN) which is one of the recent generations of ANN that incorporates anxiety and confidence emotions into the ANN, was used by Nourani et al., (2020b) to model roadway traffic noise. The ENN led to higher accuracy in the prediction of roadway noise than the classic ANN and some common empirical noise models (CNR, RLS90 and BURGESS). Also, the study proved that dividing the traffic volume into sub-categories could enhance performance of the roadway traffic noise model up to 12% in the verification phase. Although many AI-based models have already been utilized for roadway traffic noise prediction, and proved to be superior to both regression and empirical models, it is difficult to ascertain one particular model as a universal model that can predict roadway traffic noise with higher accuracy in all countries since different places have different traffic composition and characteristics. To overcome the constraints of the single models in modelling engineering processes like traffic noise, hybrid models have begun to attract attention of the researchers. Combining different models for predictions was found to be effective in improving the prediction accuracy in some other engineering and financial problems (e.g. see Nourani et al., 2011; Zhang et al., 2019).

Statement of the problem

Traffic noise can be measured physically in the field or using some verified estimation models. The physical measurements are costly, dangerous, time consuming and sometimes infeasible for large metropolitan areas. Based on this reason, researchers continuously work on improving the performance of the estimation models for obtaining estimated noise level with higher accuracy. Some of the classical models developed for prediction of vehicular traffic noise are the Italian C.N.R model, French NMPB-Routes-96, the German RLS 90 model, the English CoRTN Procedure, the United States FHWA model, the Japanese ASJ RTN-model, and Nord 2000 used by the Scandinavian countries (Garg and Maji 2014; Can and Aumond 2018). The major limitations of the empirical models is lack of generalization ability and are believed to be effective and reliable only in countries having similar traffic composition and characteristics with the countries the models have been developed for (Federal Highway Administration 2016).

To overcome the limitations of the empirical model, artificial intelligence (AI) based models which are robust in modelling complex non-linear processes with an acceptable level of accuracy motivates many researchers to apply different AI models in modeling vehicular traffic noise. Even though the AI methods may provide promising results, it is known that under different conditions, different methods may provide different results for a certain problem and selection of the most appropriate model to predict noise in particular region is challenging owing to its complex nature.

Aims and Objectives

Aim

The aim of the study is to develop AI-based models for the prediction of vehicular traffic noise in Nicosia, North Cyprus. The aim of the study can be achieved through the following objectives.

Objectives

- To determine the relationship existing between the input parameters and the vehicular traffic noise in the study area through nonlinear sensitivity analysis.
- To develop and compare performance of 4- single black models (ANN, ANFIS, SVR, MLR) for prediction of vehicular traffic noise.

- To develop and apply ensemble models, linear-nonlinear hybrid models and a new generation of ANN (i.e., Emotional ANN) for enhancing the efficiency of the single black box model in the prediction of vehicular traffic noise.

- To evaluate the relevance of vehicular traffic noise in the prediction of $PM_{2.5}$

Hypothesis

Following are the hypotheses in this study;

- AI-based models predict the traffic noise level with higher accuracy than the empirical models and the conventional MLR.
- The EANN, Hybrid and ensemble modelling could increase the prediction accuracy of the distinct AI-based models.
- The accuracy of the $PM_{2.5}$ models increases with inclusion of traffic noise as an input parameter.

Significance of the study

The models proposed in this study will provide higher prediction capability than both the empirical models and the single AI models by combining outputs from different models through ensemble. This is because the following benefits can be derived from ensemble of many models i) The difficulty in model selection of the appropriate model for noise prediction has been removed since the ensemble models are capable of providing result that is even better than that of the best single model (Nourani et al. 2020a) ii) By conjoining the results of linear models and the nonlinear models (through ensemble, hybrid), the linear and the nonlinear patterns of the process could be captured effectively (Nourani et al. 2019a). Ensemble models are believed to provide results with low error variance and increase the prediction capability by combining the unique features in each model. Therefore, the proposed methodology (ensemble approach) can be used even in countries with different traffic composition and would help stakeholders to predict noise level with higher level of accuracy.

Limitation of the study

The data used for modelling the traffic noise in the study was collected during the morning, afternoon and evening peak hours and only at straight tangents of the road which is at a reasonable distance from intersections.

Chapter I Summary

The chapter outlined the structure of the study by considering the research background, problem statement, significance of the study, research hypothesis as well as the aim and objectives of the research.

CHAPTER II

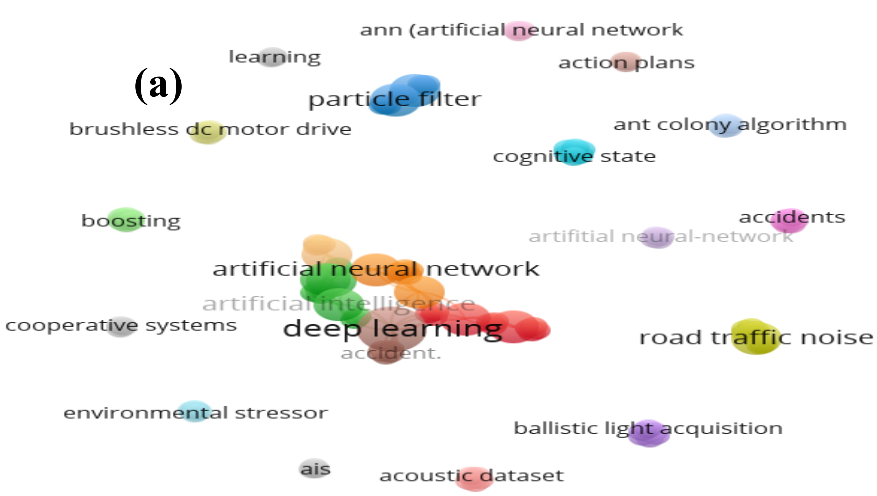
Literature Review

For the past seven decades (i.e., since 1950s), different arithmetic models were developed by scholars in an attempt to get better, cost-effective, and faster predictions regarding roads traffic noise measurement due to these models' suppleness and heftiness compare to other usual measuring approaches that are physical in nature (Ali et al., 2019).

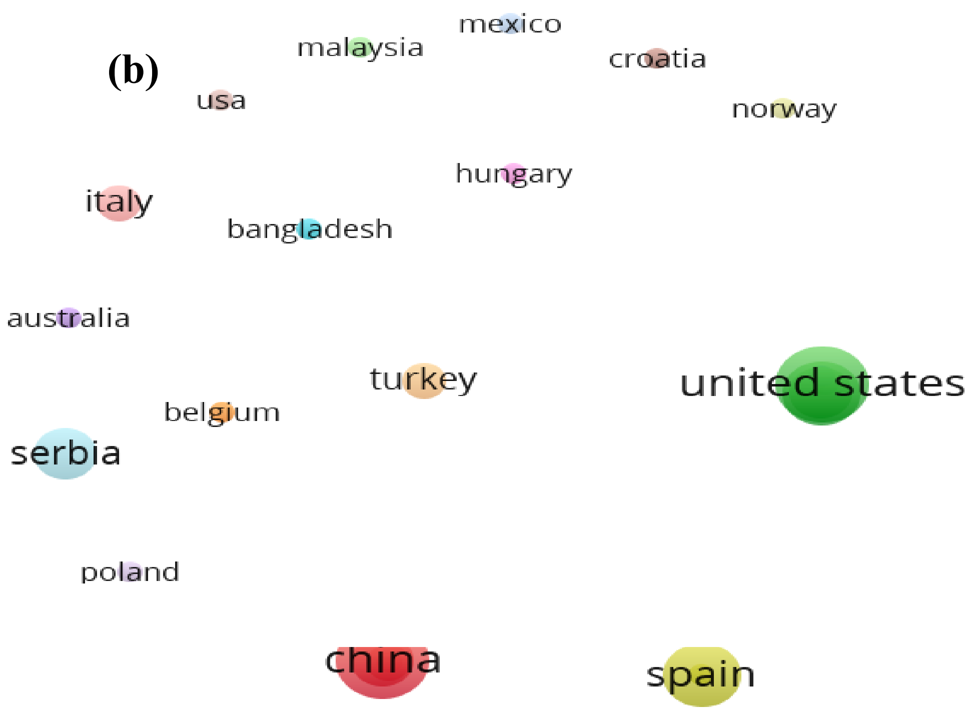
A computerized search method was used for conducting the literature review. The Near East University Grand Library online resources was used to search relevant research articles published in the Scopus, Springer, ScienceDirect and Web of Science databases using the following keywords: "noise", "vehicular", "road", "artificial intelligence", "ANN", "ANFIS", "SVM", "hybrid" and "modelling". Based on the extensive literature search, it was found that, there is need for substantial attention on road traffic noise modelling using the viability of AI based models. Figure1a shows the main keywords of over 120 literature and likelihood occurrences, while Figure 1b indicating the important of this topic especially in the world and North Cyprus in particular. The conceptual approach of modelling road noise using the proposed models in this work would be of interest and benchmarks to the researchers and scientist.

Figure 1

The algorithm results for the (a) Scopus database research for the surveyed keywords (b) the region/counties employed the road traffic noise research frequently



(b)



Empirical Models for Noise Prediction

The empirical models were the early models to be developed by scientist in the prediction of traffic noise. The most commonly used empirical models for prediction of roadway traffic noise are the Italian C.N.R model, French NMPB-Routes-96, the German RLS 90 model, and the English CoRTN Procedure. Other models include the United States FHWA model, the Japanese ASJ RTN-model, and Nord 2000 used by the Scandinavian countries (Garg and Maji, 2014; Can and Aumond, 2018). The RLS90 model was developed in Germany and is still the most relevant empirical model in the country. The equivalent noise level at 25m from the noise source under idealized traffic condition is expressed as the function of the traffic flow and percentage of heavy vehicles. The CNR model was developed by the Italian "Consiglio Nazionale Delle Ricerche" by modifying the German RLS90 model. In the CNR model, the traffic is categorized into subcategories taking into account their different acoustic contributions to the overall traffic noise level (Garg and Maji, 2014). The first application of the Burgess model was in Sydney, Australia. The model expresses the noise level as a function of traffic flow, distance of the source from the receiver and percentage of heavy vehicles in the traffic (Quartieri et al. 2009). The inputs used in most of these models are traffic characteristics irrespective of the country or region. The empirical noise models for the prediction of traffic noise are believed to be reliable in predicting the traffic noise of the country they are designed for, but cannot perform well in places with significant variation in the traffic composition (Federal Highway Administration, 2016).

ANN Models for Traffic Noise prediction

Parbat and Nagarnaik, (2008) used ANN to predict the roadway traffic noise of 16 different interrupted and uninterrupted locations in Yavatmal city India (intermediate city) using vehicle composition, total traffic, carriageway width, a distance of the receiver from the pavement as input variables. Datasets extracted from the three hours observation during morning and evening peak hours were used for the model. The developed ANN model has shown better performance than regression model with RMSE and MAE as performance parameters, the research also hinted RMSE to be a better performance parameter than MAE.

Hamoda, (2008) modelled the noise level at construction sites in Kuwait using BPNN and GRNN to predict models for environmental impact assessment. 180 data sets from 33 different construction sites comprising of the project stage, project size, project type, distance from the site and type of equipment used were selected for training and testing of the models. The GRNN performed better than the BPNN to its speed and robustness in prediction.

Genaro et al. (2010) used ANN to model noise level in Granada Spain with 289 data sets obtained from 12 street. The model has 25 input variables with noise level as the output. The model was further simplified using principal component analysis to 11 input variables by removing variables with less significance. The result shows a slight decline in the goodness of fit by reducing the input variables. The results of the ANN proved to have high performance than the conventional models.

Givargis & Karimi, (2010) employed the use of ANN to model the hourly weighted equivalent sound pressure using data collected from 50 sampling points in Tehran. The noise data was collected at distance of 4m from the edge of the round at a height of 1.4m for speed not exceeding 75 kmph. Total traffic flow, percentage of heavy vehicles, gradient and hourly mean average speed were used as the model's inputs. The ANN was found to be capable of predicting the traffic noise with acceptable level of precision.

Al-mutairi, (2012) compared the performance of three different modelling techniques (the regression models, the BPNN, and the GRNN) for the prediction of traffic noise using 620 data set from four different roadways in 4 different districts from 2007-2008. Vehicle's speed, equivalent number of cars per hour, percentage of heavy vehicle, roadway width and the average height of buildings facing the road were used as inputs variables of the models. The BPNN proved to have higher performance, however when the GRNN was trained with genetic algorithm, it was found to have a high performance than the BPNN.

Arora (2012) used ANN model for the prediction of traffic noise along 90km road of NH2 in India with 95 data set from 88 different location using traffic volume, percentage of heavy vehicles and speed as input parameters. The ANN shows high prediction capacity for the model which can be applied for environmental impact assessment.

Kumar et al. (2012) reviewed various ANN models developed using different variables in many countries around the globe, the result shows better performance of the ANN models over the conventional and statistical models' due to nonlinear relationship between noise generating factors and the noise level. The problem attached with getting a wrong correlation between the noise level and the causative factors when a wrong data or an error was supplied to the neural network can be solved by using 2-level layers in which one layer (learning vector quantization) will serve as a filter while at second level the BPN predicts the sound pressure level. The research further recommends using particle swamp optimization, fuzzy logic and genetic algorithms for modeling road traffic noise

Kumar et al. (2014) used Levenberg–Marquardt (L–M) algorithm to train several multi-layer FFNN for the prediction of 10-percent exceeded sound level and equivalent continuous sound level in Punjab city in India with heterogeneous traffic composition consisting of many two-wheelers. The models input parameters includes percentage of heavy vehicles, the logarithmic value of total vehicle flow and average speed recorded for 1hr duration on different dates. The data was divided into training data consisting of 36 datasets and 10 sets for verification of the model out of the 46 different observations made during the study. The best model was obtained using a 3-8-2 structure which gives highest value of the correlation coefficient and least estimation error in both calibration and validation stage. The ANN model gives higher accuracy with percentage error values of -0.8 to 1.0 for $_{L10}$ and -1.5 to 0.9 for L_{Aeq} in training while Multi regression models have percentage error ranging from -4.2 to +2.7. The result of the t-test verified ANN model to have better prediction capability than the regression model at 5% significance level.

Zilioniene et al. (2014) recorded noise data for 24hr a day for six months using five sensors along the road distance and stored in a trained GIS system. The data was processed using ANN to model the traffic noise of a freeway stretching 20 km long. The input variables used in the model the noise level (L_{eq}) consists of operational speed (V_{85}), a distance of the vehicle from the sound sensors, traffic flow. The ANN model was found to be more reliable with fewer residuals in predicting traffic noise compared to the 9 common conventional models.

Nedic et al., (2014) modeled the equivalent traffic noise level of a 2-lane 2-way road in an urban city in Serbia with 120 data sets of one-hour observations comprising the traffic noise level, traffic volume and classification and speed using ANN and compared it with some statistical model. Statistical results show higher prediction capacity of ANN model than all the statistical methods (C.N.R. models, Griffiths, Fagotti, and RLS90, C.S.T.B.).

Cirianni & Leonardi (2015) developed a neural network model to estimate the traffic noise level in the city of Villa S. Giovanni, Italy using data set obtained from 14 survey sites on an uninterrupted road segment having a reasonable distance from stop signs and intersections. The models' inputs were traffic volume, distance from the noise source, percentage of heavy vehicles and speed. The research affirmed that ANN can predict noise traffic with satisfactorily even using restricted database. The research further recommends inclusion of more parameters such as ground type, classification of vehicles, road surface and reflective surface.

Garg et al. (2015) demonstrates how artificial neural networks may be used to estimate the equivalent continuous sound level (LAeq) and the 10-percentile exceeded sound level (L10) created by traffic noise in different parts of Delhi. The measured data was used to train, validate, and test a model based on a back-propagation neural network. The research demonstrates that the algorithm can accurately anticipate traffic noise levels on an hourly basis. In terms of overall traffic flow and equivalent traffic flow, a comparison study demonstrates that neural networks outperform numerous linear regression models. The study's prediction model might be useful for traffic noise forecasting and noise abatement in Delhi.

Garg et al. (2016) used ARIMA and ANN were to model the daily traffic noise level for both day and night time using one-year daily data in India. The ANN performs better than ARIMA and can be employed for predicting traffic noise level with the high level of accuracy. This can replace the expensive long-term continuous traffic noise monitoring. The research further recommends exploring potentials of using the hybrid model on dynamic time-series database for predicting sound levels

Singh et al. (2016) applied ANN, generalized linear regression, decision tree, and random forest to model the equivalent sound pressure at three different locations on a flat road in the city of Patiala India with 502 data set comprising hourly traffic volume, average speed of vehicles and percentage of heavy vehicles as input variables. Evaluation of the model performances shows random forest to have higher prediction capacity than the other three soft computing approaches. It is faster, cost-effective and more accurate than the classical models. Therefore, policy and decision makers, urban authorities' environmental managers, town planners should adopt it, and other stakeholders involved in environmental management should adopt the use of the ANN based models.

Huang et al. (2017) investigated the acoustic comfort of multistory buildings and developed a noise analysis model for multistory structures, particularly those located near urban expressways. The research was conducted in three stages. First, using noise measurement equipment, a survey of the noise levels on each floor of multistory buildings along a free flow highway was carried out. A C-weighted network was also employed in combination with an A-weighted network to assess low frequency noise, which is less noticeable in most surveys and was hence less studied. Second, the rule of change for noise indicators on the vertical plane was investigated. The acoustic amenity of multistory structures was thoroughly and rigorously investigated using a combination of change rule and frequency spectrum analysis. In the final stage, an ANN was used to generate a model for the prediction of vehicular traffic noise for multistory buildings along a highway. It is important to note that the comparison between the produced model, the FHWA model, and the observed data reveals that the developed model fits the observed data better compared to the FHWA model at the 5% significance level. The developed model might be utilized for acoustic amenity assessments and model building. It would be able to use the information to create design references for urban expressways and buildings.

Hamad et al. (2017) modelled the vehicular traffic noise of the city of Sharjah in the UAE using ANN to ascertain the effect of temperature on the traffic noise. Two major models, one with temperature as an input and the other without temperature were modeled using 420 hours observation data set from three different locations. Other model input variables used are traffic volume and classification, average speed, distance from the edge of the surface. Performance of the model was improved by incorporating temperature into the model with R^2 increasing from 0.990 to 0.995 and mean absolute error decreasing from 0.5500 to 0.4980. Illuminating the ANN black box with using visual explanation, sensitivity analysis and comparative importance of variables (Garson's algorithm and R^2 based metric) to ascertain the effect of each of the variables on the traffic noise ranked distance from the edge, volume of light vehicles, road temperature, average speed and heavy vehicle to be the factors affecting the noise level as 1st, 2nd, 3rd, 4^{th,} and 5th respectively in their order of significance. The ANN model outperformed the conservative models (Ontario ministry of transport traffic and the Basic statistical traffic noise model) having higher determination coefficient and lower mean absolute error for both models with surface temperature effect and the one without temperature effect.

Mansourkhaki et al. (2018) developed roadway noise model for the urban city of Tehran using the ANN model by utilizing a data consisting of 51 observations from 34 different locations. The model has 9 input variables consisting of hourly traffic volume, average speed, vehicles’ classification grouped into four classes (cars, vans & pickup, heavy vehicles and motorcycles), gradients, density of building facing the observer and building reflection factor (BRF) and equivalent continuous sound as the model output. The ANN model shows superiority when compared with regression models and other classical models such as IRAN model, RLS90, C.N.R, CORTN. The model superiority was affirmed by a paired t-test where the t-value for ANN-model was far less than the critical t-value compared to the regression model. The paper also shows the importance of including the building reflective factor (BRF) in improving the efficiency of the ANN model.

Tomić et al., (2018) used 270 data set for 15minutes observations from 18 streets across the city of Nis, Serbia to model vehicular traffic noise in Serbia using ANN. Each data set comprises of traffic characteristics data consisting of the number of cars, medium and heavy trucks, motorcycles, buses and distance from the center of the road axis. 188 datasets were utilized for calibration while remaining 87 were employed for verification and testing of the model, this data set is large compares to other data researches. The paper compares the result of the ANN-based model with four conventional models (French, CNR, RLS90, and Nordic). The noise levels predicted by the constructed ANN were compared to experimental data and those from commonly used mathematical models. The statistical study reveals that using ANN to forecast traffic noise levels not only improves accuracy, but also reduces the frequency of predictions with errors greater than 3 dB.

Kumar et al. (2018) used a multilayer feedforward backpropagation neural network (FFBPN) to model the equivalent noise level and 10-percent exceed sound level in Punjab using 133hr data set comprising of traffic volume, average speed and percentage of heavy vehicle in the traffic, obtained on a 2-lane highway in Patiala (Punjab) city, India. The ANN model proved to have high prediction ability in predicting traffic noise.

Ali et al., (2019) compared the performance of four AI-based models (regression decision trees, SVM, ensemble trees, and ANN) and conventional regression model in predicting the traffic level of Sharjah Dubai, the results proved superiority of the AI-based models over the conventional models.

Bravo-Moncayo et al. (2019) formulated a model for forecasting roadway traffic-noise irritation based on noise exposure levels, noise perception, and demographics. The study employs the use of machine-learning approaches, namely ANN, multiple linear regressions and support vector machines for developing the traffic-noise irritation models. The performance of these models was compared in terms of their error rates. A traffic noise map was also created in order to assess the amount of noise exposure for the case study area. Although, it is quite evident that subjective noise perception and predicted noise exposure levels strongly influence traffic-noise annoyance, typical statistical models are unable to provide reliable predictions. The machine-learning technique demonstrated improved precision in terms of error and determination coefficients. The ANN model produced the greatest results in terms of forecasting traffic-noise irritation, with error reductions in training subsets of 42 percent and 35 percent, respectively, when contrasted to SVM and the MLR models. The error reductions for verification subsets were 24 percent and 19 percent, respectively, for the two models under study. R^2 increased by 3.8- and 2.3-times using ANN models at calibration stage when compared to MRL and SVM models respectively, and by 1.7 times using both MRL and SVM models in testing stage. Consequently, the developed model could be utilized as a more dependable and precise instrument for measuring the influence of traffic noise in urban environments, increasing the comfort of the population, and assisting in the development of appropriate public policy.

Ahmed and Pradhan (2019) used ANN model to predict and simulate noise propagation from vehicles traveling on the New Klang Valley Expressway (NKVE) in Shah Alam, Malaysia through a dense residential area. The ANN predicts how much noise is produced from cars and trucks, and a mathematical model was used to figure out how the noise will spread. The noise predictors chosen for developing the ANN model includes volumes of motorbikes, cars as well as the ratio of heavy vehicles like trucks and buses to the overall traffic volume, highway density, a light detection and ranging (LiDAR)-derived digital surface model (DSM). After that, the ANN and its hyper parameters were optimized in a systematic way using a grid search method. The noise propagation model was then created using five variables, including road shape, obstacles, distance, air particle interaction, and meteorological conditions, in a geographic information system (GIS). These five factors were used to build the model. The data used in the study was measured at 15-minute intervals. The data were analyzed by considering the lowest and highest values observed. The measurement was done eight times in a week that is morning, afternoon, evening, and midnight of Sunday and Monday which represent the working and non-working days. A radial basis function NN with 17 hidden layers was utilized to find the best model using the learning rate of 0.05 and the momentum value of 0.9. The proposed model achieved 78% accuracy with an error of less than 4.02 dB (A). Overall, the developed models were uncovered to be good tools for measuring traffic noise in dense cities.

Chen et al. (2020a) collected longitudinal gradient data from numerous highways in Chongqing County’s Mountain cities to investigate the influence of gradient on traffic noise prediction. To investigate the noise characteristics of a wide variety of road gradients and to develop an artificial neural network-based traffic noise prediction model, average vehicle speeds, traffic volumes, ratio of heavy-vehicles, road slopes, and the equivalent sound pressure levels corresponding to those values were collected from the field. The best artificial neural network (ANN) model developed was compared with two traditional models. According to the obtained result, a one-hidden-layer artificial neural network model was uncovered to be acceptable for the prediction roadway traffic noise in mountain cities and perform much better than the traditional models. ANN models with high determination coefficients and low mean-squared errors (e.g., 0.2708 dBA) were found to be the most effective. The findings of this study also revealed that road gradients were important for developing traffic noise prediction models.

A traffic noise prediction model for mountainous cities was developed by Chen et al. (2020b) utilizing an ANN model. The ANN model was trained and validated using data obtained from a municipal road in Chongqing, a mountainous city. The per-vehicle noise level, vehicle velocity, vehicle type and highway gradient were the predictor variables. The updated HJ 2.4-2009 model with the gradient adjustment coefficient has a much higher R^2 values for rocky cities than the traditional model, according to the findings. Furthermore, the ANN-based noise prediction model outperformed the empirical predictive equations in terms of accuracy.

Tan et al. (2020) used a machine learning model that used the BPNN approach to predict a vehicle's noise limits for future changes to the (United Nations Economic Commission for Europe (UNECE R51) regulations using past data. The Levenberg-Marquardt method was adopted for training the BPNN model which at the same time choses the validation and test data at random to evaluate whether there is any association and how accurate the predictions are. For ensuring accuracy of the proposed model, acceleration noise limits from six historic data are used for training the model, and the noise limits at the seventh version can be predicted and validated. As the results achieve a required accuracy, vehicle noise limits in the next revision as the future eighth version can be predicted based on these data. It can be found that the obtained prediction results are much close to those noise limits defined in current regulations and negative error ratios are reduced significantly, compared to those values obtained using a quadratic regression model. The prediction results are quite near to the noise limitations specified by existing laws, and the negative error ratios are far lower than using a quadratic regression model.

Kim et al. (2021) used a 3D urban model and data on road-traffic noise levels from a normal noise map of city A (Gwangju) to develop an ANN and an ordinary least squares (OLS) model. The newly created ANN and OLS models were tested in City B (Cheongju), and the resulting statistical noise map was compared to the city's existing normal road-traffic noise map. The OLS model removed multi-collinear urban form indicators, and among the remaining urban forms, road-related urban form indicators like traffic volume and road area density were discovered to be relevant variables in forecasting road-traffic noise levels in design of quiet city. The OLS model has a propensity to underestimate road-traffic noise levels, whereas the ANN model has a tendency to overstate them, according to comparisons of the statistical ANN and OLS noise maps with the normal noise map.

Ranpise et al. (2021) examined the ambient noise levels along key arterial roads in Surat, compared them to mandated criteria, and used artificial neural networks to construct a noise prediction model for arterial roadways. Each of the ANN models was constructed using data received from a different route, and a final model was developed utilizing data obtained from all three roads together. The estimated output results from the model of Adajan-Rander were found to have a better correlation than the other two models, with an MSE of 0.789 and an R^2 value of 0.707 for the predicted output results on three arterial highways. Although there is a modest decline in the mean squared value (MSE), it is not statistically different from 1.550 when the combined model is used, with R^2 remaining unchanged at 0.755. However, because of the diversity of data utilized in its training, the prediction made by the combined model may be implemented.

ANFIS Models for Traffic Noise prediction

ANFIS was used to model the vehicular noise of two cities in Italy (Villa S. Giovanni and Messina) having different traffic characteristics and population using a dataset consisting of 176 observations. ANFIS has shown better performance in predicting the traffic noise than the traditional regression models used in literature. The prediction error and the standard deviation of the error for the developed model were found to be 0.59 and 0.77 dB(A) for the training; 0.97 and 1.04 dB(A) for the validation; and 1.11 and 1.15 dB(A) for the testing indicating an acceptable level of fit (Cirianni and Leonardi 2011).

ANFIS was used to develop two models one for vehicle classification (ANFIS-TC) based on their acoustic signature and the other prediction of traffic noise (ANFIS-TNP). The classification model also computes total number of vehicles traversing the observation point. The ANFIS-TNP has three inputs equivalent traffic volume from the ANFIS-TC model, equivalent vehicle speed and honking. The result of the statistical analysis ANFIS-TC shows 100% accuracy in vehicle classification. The confusion matrix shows that the model classifies 34 heavy vehicles, 33 medium, and 33 light vehicles successfully in cross-validation. The ANFIS-TNP predict the traffic noise with a high level of accuracy with determination coefficient ranging from 0.968 to 0.750 for all the eight sampling locations. The research mentioned increased honking due to heterogeneous and congestion to increase traffic noise. Comparing the ANFIS-TNP model with FHWA, CRTN, and RM model shows its superiority and can, therefore, be applied in urban areas with heterogeneous traffic in assessing as well as controlling noise pollution (Sharma et al. 2018).

The traffic noise generated by the heterogeneous traffic characteristics of Nagpur city in India was evaluated using ANFIS considering speed, traffic flow and honking as the model's input variables. The R^2 value obtained between observed and estimated values for the eight different locations studied fall between the range of 0.70 to 0.95. Performance of the proposed model has demonstrated superiority over the conventional models such as regression models, Federal Highway Administration (FHWA) and calculation of road traffic noise models. The proposed model can easily be modified to predict traffic noise under different traffic conditions, hence it can be a hand tool for vehicular noise assessment (Sharma et al. 2014).

A study was conducted in Erzurum, Turkey with the aim of predicting traffic noise in urban areas using ANN and ANFIS. Similar input data sets consisting of total hourly traffic volume, number of heavy vehicles, average speeds of the vehicles were used to predict the 10-percentile-exceeded sound level (L_{10}) using both ANN and ANFIS method in order to compare the performance of the two methods. Results of the study show that the ANFIS model performed better than the ANN model in predicting the vehicular traffic noise in the urban city bases on statistical results. The R^2 value of ANFIS and ANN models were estimated to be 0.91 and 0.81 respectively. The study also concluded that the prediction of road traffic noise under heterogeneous traffic which is complex, traffic characteristics and driver behaviors cause an irregular pattern of generated noise (Codur et al. 2017).

AlKheder and Almutairi (2021) estimates roadway traffic noise levels on ring road in Kuwait by utilizing the ANFIS model. Data from 20 distinct measurement locations was gathered twice daily in the field. It yielded 480 data points for 10 variables viz traffic noise level, average speed of the heavy and light vehicles, volume of light traffic, volume of heavy vehicle, width of the road, pavement quality, heights of the buildings along the road, air temperature and highway temperature. A vision-based vehicle recognition system based on machine learning was created to aid in the data collection. The system achieved 90% accuracy, whereas the ANFIS model had an RMSE of 0.0022. For validation, the model was tested on a different path, yielding a 0.06 RMSE. The results of the single-input single-output sensitivity analysis values and that of the R^2-based metric were used to rank the nine input variables based on their relative relevance in the vehicular traffic noise prediction. The most essential component, according to the findings, was number of light vehicles, whereas volume of heavy vehicle found to be the least effective element. The fourth and seventh places, respectively, were given to air and road temperatures. Following that, four possible scenarios for traffic noise levels in 2025 were created. The results of the sensitivity analysis informed the first three scenarios. The speed restrictions on the ring road are reduced from 120 km/h to 100 km/h in Scenario I. Scenario 2 adopts high rise building to have the same effect as a noise barrier. In Scenario III, there is curfew for trucks at nighttime. Finally in Scenario IV, it was assumed that there is no noise control mechanism at all. A noise level of 76.01, 80.66, 83.36, and 84.56 dBA were obtained, respectively for scenarios I, II, III and IV. A traffic noise control system can plainly be observed to successfully minimize traffic noise.

GA Models for Traffic Noise prediction

Gundogdu et al. (2005) studied the impact of vehicular traffic categories on the vehicular traffic noise pollution in Erzurum, a miniature city in eastern part of Turkey with a population of over 400,000 people. Noise measurements and vehicle counts were undertaken over 12 hours at the city's four busiest traffic locations. Using information of category class of the vehicles and maximum allowable noise emissions of each kind of vehicle, two models based on genetic algorithms that might be used as tools for in-city traffic flow redesign have been developed. The models were validated using some of the noise data. The new and prior models' predictions were compared to measured traffic noise levels, and a good agreement was discovered.

Rahmani et al. (2011) developed two models for estimating road-traffic noise pollution in Mashhad's city. The model's parameters were chosen to be traffic volume, composition, and speed. The vehicles were classified into three sets: light automobiles, medium trucks, and heavy vehicles. Each group's reference emission level was calculated experimentally using perpendicular propagation from the traffic road's middle lane. Noise levels, vehicle flow, and composition were all measured at the same time. Genetic algorithms have been used to offer two mathematical models that may be used to calculate the Leq. These models have been tested on data that contains noise. The observed traffic noise was compared to estimated traffic noise using developed models, and a pretty good agreement was found. The models proved to be accurate to within 1% error and could be used to forecast road traffic noise.

Hybrid models

Khouban et al. (2015) proposed an expert system based on Artificial Neural Networks to model road traffic noise. Feed-Forward Neural Networks (FFNNs) trained using the Levenberg-Marquardt back-propagation technique was used. The models were evaluated using two statistical performance measures mean squared error (MSE) and coefficient of determination (R^2). Traffic noise modelling simulates the noise level at a receptor location generated by a source of traffic emission as a function of traffic situations, road gradient, road dimensions, speed, and the height of buildings surrounding the road. The ANN model suffers from the curse of dimensionality because to its large number of input variables. The Hybrid Genetic Algorithm-Gamma Test (GA-GT) was also used to choose appropriate model inputs as a data pre-processing technique. The input variables were typically selected using genetic algorithms, which reduce the overall number of predictors in the process. Using the hybrid model, six of the twelve sets of predictor candidates were used as input variables in the ANN model. When the results of the hybrid model (ANN-GA-GT) is compared to the results of the ANN model, it is obvious that the hybrid model has more advantages, such as improved performance prediction, cheaper future measurement costs, and reduced processing and data storage requirements. As a result, the ANN-GA-GAMMA model was recommended for predicting traffic noise levels.

Other AI-based Models for Traffic Noise prediction

Huang et al. (2019) proposed a Laplacian score-deep belief network (LS-DBN), which is a novel intelligent acoustic model based on deep neural networks (DNNs). The LS-DBN was used to test the sound quality of EV interior noise. Internal noises from ten electric cars were captured on eight various road surfaces, and subjective evaluations were conducted to confirm the efficacy of the proposed method. Furthermore, utilizing the LS-DBN, noise features were adaptively extracted, and the adaptively extracted features were compared to manually extracted features. The performance of the LS-performance DBNs was compared to a standard DBN and BPNN. In terms of accuracy, stability, and efficiency, the proposed LS-DBN model surpasses the classic DBN and BPNN models, according to the findings. As a result, the LS-DBN is capable of making precise forecasts.

The Land use regression (LUR) model was used by Liu et al. (2020) to assess noise exposure in the environment. The researchers compared noise estimates from the RF and LUR models to quantify ambient noise levels in five Canadian cities using the random forests (RF) model. At the global (multi-city) and local (specific city) scales, a total of 729 measurements and 33 built environment-related variables were utilized to quantify spatial variation in ambient noise. Noise estimations from the RF global model explained a larger proportion of variation (R^2: RF = 0.58, LUR = 0.47) with fewer root mean squared errors (RF = 4.44 dB(A), LUR = 4.99 dB(A), according to leave one out cross-validation. At the city scale, cross-validation showed that the RF models performed better in general than the LUR models. We discovered that noise levels in Montreal and Longueuil were higher than in other significant Canadian cities when we used global models to predict noise levels at the postal code level.

Lu et al. (2019) developed structural equation models using field data from measurements in Dalian City, China, to study the mediated influence of road features on traffic noise through traffic flow. Microscopic and macroscopic traffic simulations were used to make paired comparisons of situations for further investigation. When it comes to the number of vehicles in a group (NVG), the results suggest that lane number has the greatest impact on traffic noise. More lanes signify higher traffic demand as a result of the linked metropolitan region, which raises the NVG and as a result increases noise intensity while decreasing noise amplitude. The suppression effect determines the impact of road segment length (RSL) on traffic noise. Higher vehicle speeds are possible with a longer RSL, resulting in increased noise intensity and lower noise amplitude. As a result, traffic flows disperse more quickly, lowering the NVG and reducing noise intensity while boosting noise amplitude. Road junctions (RJ) have a significant direct impact on both noise intensity and noise amplitude, which are both likely to grow when autos accelerate or brake in the midst of a road section. When it comes to improving the quality of life in urban areas, these findings may be used as a guide for local governments and urban planners.

Lan et al. (2020) suggested a technique for mapping the spatiotemporal distribution of urban road traffic noise that involves obtaining representative road traffic noise maps for various times. The technique is based on the suggested noise spatiotemporal distribution model, which includes two time-dependent variables: traffic density and speed, as well as spatiotemporal features generated from multisource data. The procedure involves the following three steps. First, the law of sound propagation is used to create the spatiotemporal distribution model for urban road traffic noise. Secondly, outlier detection analysis was used to derive temporal features from traffic flow detecting data and E-map road segment speed data. Finally, an efficient approach is used to calculate the noise distributions for different periods, which can save up to 90% of the processing time. In addition, a validation experiment was carried out to assess the suggested method's correctness. The procedure is effective since the mean absolute error is just 2.26 dB[A], which is within an acceptable range.

Sharma and Vig (2019) used a fuzzy logic-based active noise reduction system to assess prominent vehicular sounds in Chandigarh, India, under peak traffic conditions in order to reduce disturbances. A sound level meter was used to record the sound pressure level at peak traffic hours of the day. Horns on cars were identified as a common source of high-volume noise. Horn noise signals from buses, automobiles, two-wheelers, and three-wheelers were recorded. A Fuzzy Logic based Active Noise Control (ANC) system was constructed in MATLAB software and used to reduce recorded car horn emissions. The performance of the Fuzzy Logic based active noise control system for noise reduction is compared using error plots, signal to noise ratio (SNR), and mean square error (MSE). The proposed Fuzzy Logic-based ANC system lowers the noise levels of a bus and a two-wheeler by 23 dB(A) in each case. Noise levels are reduced by 28 dB (A) and 25 dB (A) for vehicle and three-wheeler horns, respectively. The fuzzy-based ANC system works well at decreasing noise to acceptable levels, and it may be utilized in real time to meet noise regulations.

Yin et al. (2020) trained four data driven models namely linear regression, random forest, extreme gradient boosting, and a neural network. to predict noise with 20 m resolution using A-weighted equivalent noise (LAeq in decibels dB), data from hour-long foot journeys around 16 locations in Long Beach, California. The models used traffic data, road network attributes, weather conditions, and land use type as input variables. In terms of validation, extreme gradient boosting beat out all other machine learning models (leave-one-route-out R^2 = 0.71, RMSE of 4.54 dB; 5-fold R^2 = 0.96, RMSE of 1.8 dB). The most important predictor of noise was local traffic volume, followed by road characteristics, land use, and environmental parameters including humidity, temperature, and wind speed. The findings show that combining on-foot mobile noise monitoring with machine learning methodologies allows for extremely accurate prediction of small-scale spatial patterns in traffic-related noise in a mixed-use metropolitan zone.

Zhang et al. (2021) used deep learning techniques to find the best machine-learning model for forecasting traffic noise from real-world traffic data using multivariate traffic variables as input. A comprehensive search of recurrent neural networks (RNNs) was conducted to model time series traffic data acquired during an experimental campaign at an inner-city roundabout, which included both video and audio traffic data. The paper went into great depth about data preprocessing, including how to develop the necessary input and output for a deep learning model. The researchers looked into several RNN designs, such as many-to-one, many-to-many, and encoder–decoder architectures. In addition, the gated recurrent unit (GRU) and long short-term memory (LSTM) were studied in depth. The findings showed that a multivariate bi-directional GRU model with a many-to-many architecture performed best in terms of accuracy and computing efficiency. Because of the generated enormous data by smart cities, the trained model might be promising for a future smart city idea; using the suggested model, real-time traffic noise forecasts could be possible using just traffic data gathered by multiple sensors in the city. The prediction of excessive noise exposure can assist regulators and policymakers in making early choices to reduce noise levels.

Based on a simulated sound level function, Afandizadeh and Gharehdaghli (2021) developed a steady-state model for estimating L10(h) on free-flow highways. In the simulation process, REMELs were first utilized to determine the sound level produced by a single vehicle at a given distance. Following that, a random distribution was employed to construct a time-dependent function for monitoring sound level as each vehicle approached the receptor. After that, data from the simulated sound level function was used to calibrate a steady-state model. Based on traffic volume, average speed, distance, fraction of heavy trucks, and road segment angles, the model was created to estimate L10 (h). Finally, the accuracy of the new model was determined by comparing it to the observed data. In order to further analyze the recommended model, the CoRTN model was employed to calculate the values of L10(h). The proposed model had a 0.96 dB A mean absolute error, while the CoRTN model had a 1.71 dB A mean absolute error. The new steady-state model offered better precision and fewer constraints than prior steady-state models since the observed data were not used for calibration and the new steady-state model was based on a created sound level function. The utilization of measured data to calibrate traffic noise models is decreased when the suggested approach is used. Instead, there is a nearly limitless amount of data, which allows for more precise correlations between L10(h) and the model's independent variables.

Khajehvand et al. (2021) used several factors from traffic characteristics, geometric features, pavement surface quality, and traffic management to simulate the level of vehicular traffic noise at junctions. A drone was deployed to film traffic flow while a sound level meter was utilized to measure traffic noise. At signalized T-intersections, cross-intersections, and roundabouts, regression modeling was utilized to find the relevant factors and their contributions to the produced noise level. The findings revealed that the overall traffic volume, as well as the number of cars, pavement condition index, and speed, have a substantial influence on noise levels. Furthermore, traffic noise levels are greater at roundabout departure approaches than at roundabout entry approaches. Furthermore, unexpected occurrences and non-lane-based behavior resulted in a significant rise in the maximum sound level as departure approaches.

Chapter II Summary

The chapter gives detailed and comprehensive report of the previous works done in the literature in order to provide background knowledge on the research topic. The chapter studied both empirical models and artificial intelligence-based models with much emphasis on the different artificial intelligence-based approaches like the artificial neural network, support vector regression, genetic algorithm, adaptive neuro fuzzy inference system and hybrid models. It was found that the ANN was the most widely used model used for the prediction of vehicular traffic noise.

CHAPTER III

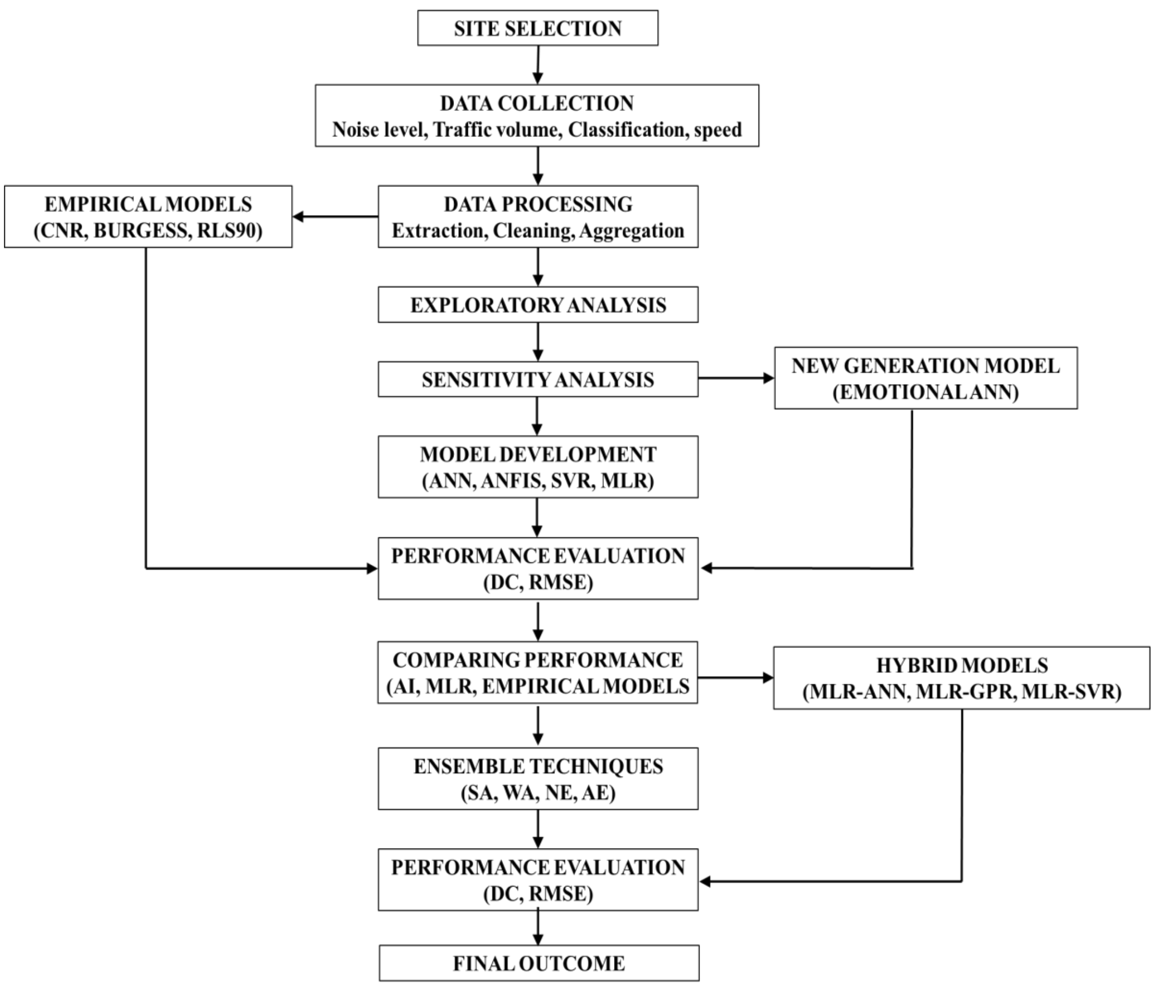
Methodology

Phase I methodology

The methodology for conducting this study involves five stages as shown in Figure 2. This involves site selection, data collection and pre-processing, exploratory analysis of the data, noise mapping sensitivity analysis, development of 4 single black-box models and development of 4-ensemble models.

Figure 2

Proposed methodology for phase I



Site selection and data collection

The data for the study were collected from Nicosia city in North Cyprus between 4th February and 30th April 2019. The study area has a total population of 94,824 which is around one-third of the population of North Cyprus, according to the latest census which was performed in 2011 (Statistics and Research Department Nicosia 2017). The number of registered vehicles in Nicosia is around 182,709 and non-registered vehicle are approximately 109,665 in 2017 (Statistics and Research Department Nicosia 2017). Data samples comprising of noise level, traffic volume, vehicle composition, speed and number of horns in 15 minutes observations were collected from 12 sampling points. The sampling points consist of 1-point on an motorway (point 12), 5-points on a major road (point 1,2,3,4,5), 2-points on a secondary roads (point 10,11) road and 4-points on a local road (point 6, 7, 8, 9) in order to have proper representation of residential, commercial and industrial areas (see Figure 3). Measurements were conducted in the morning (8:00-10:00), afternoon (12:00-14:00) and evening (16:00-18:00) hours to capture different diurnal variations of the noise. Afternoon data were not collected for sample points 8, 9, 10, and 12. This is because preliminary investigation of the traffic data at these points shows lower traffic volume in the afternoon hours compared to morning and evening hours. The observation points were carefully selected in such a way that other sources of noise apart from traffic were minimized to the barest minimum and all data were collected when the pavement is dry with relative humidity and wind speed not exceeding 80% and 5m/s, respectively. The noise data were measured continuously for 15 minutes at one-second interval using a class II sound level meter (SLM) placed at a height of 1.2m and at a distance of 3-5m from the road edge depending on the space available as shown in Figure 4 for example. Simultaneously with the equivalent sound level, the traffic data were recorded using a video camera. The total traffic volume and the vehicular composition (classified into cars, buses, pickup/van, trucks, motorcycles) were obtained by playing the video on the computer screen and counting the number of each vehicular traversing the sampling point in the time period (15 minutes). The average speed of the vehicles was also calculated from the video analysis by measuring the travel time required for the vehicles to traverse two marked points of 50m distance on the pavement while the number of horns in the time period was manually recorded.

Figure 3

Study area map and sampling points

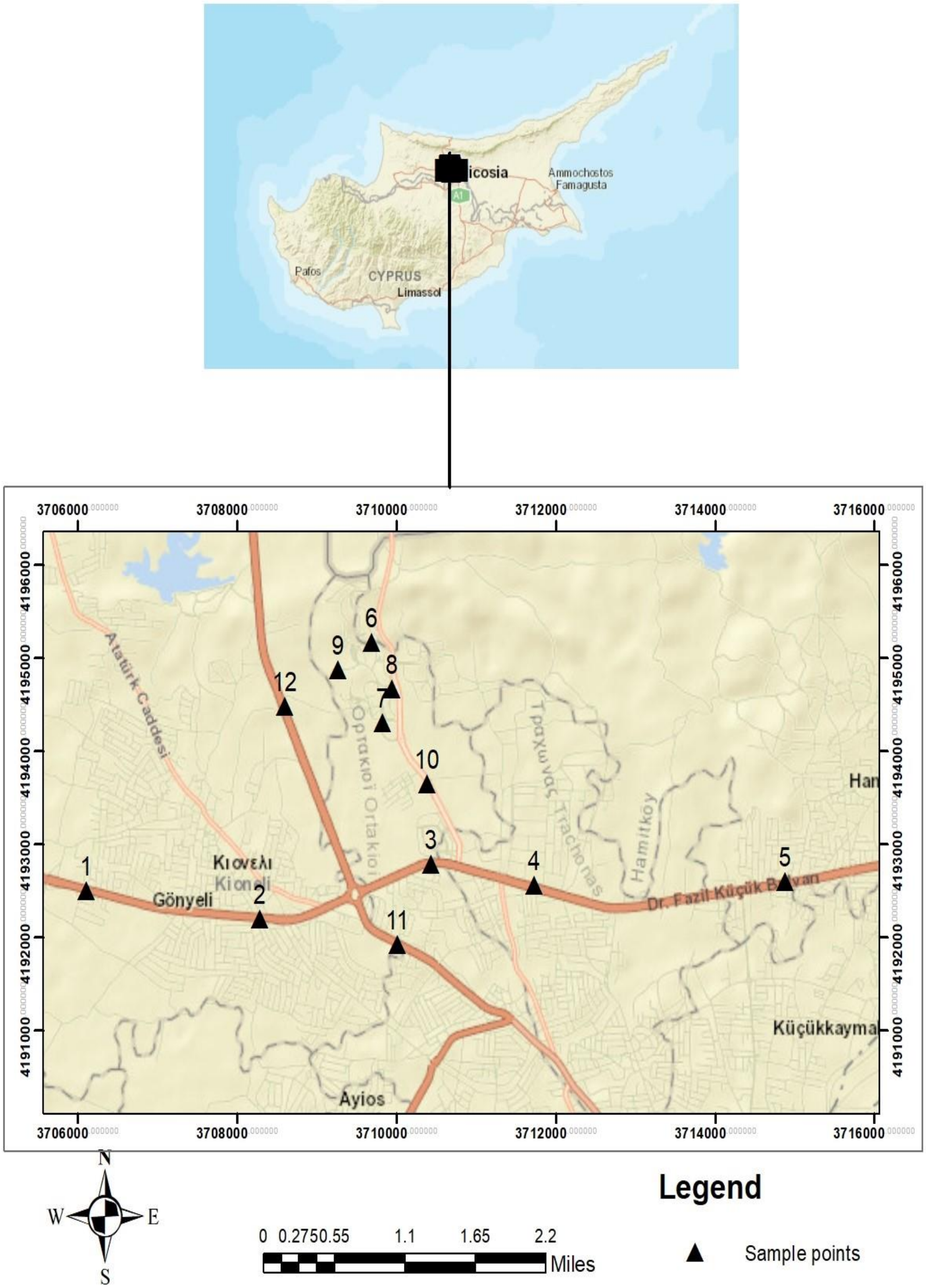
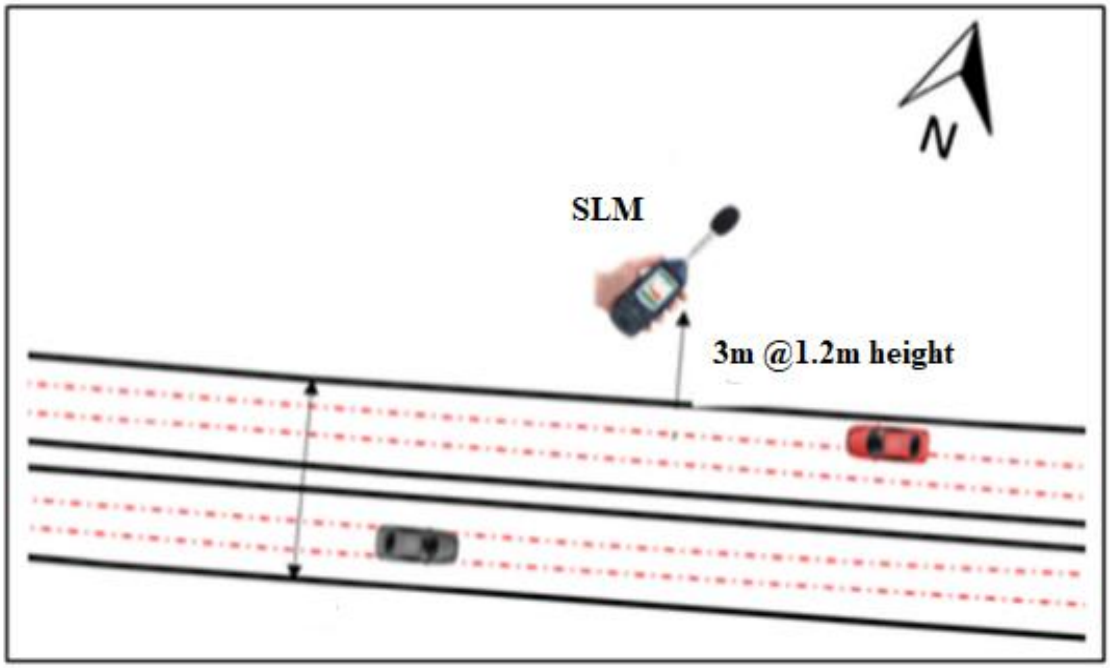


Figure 4

Data collection Measuring noise using the sound level meter at the roadway section



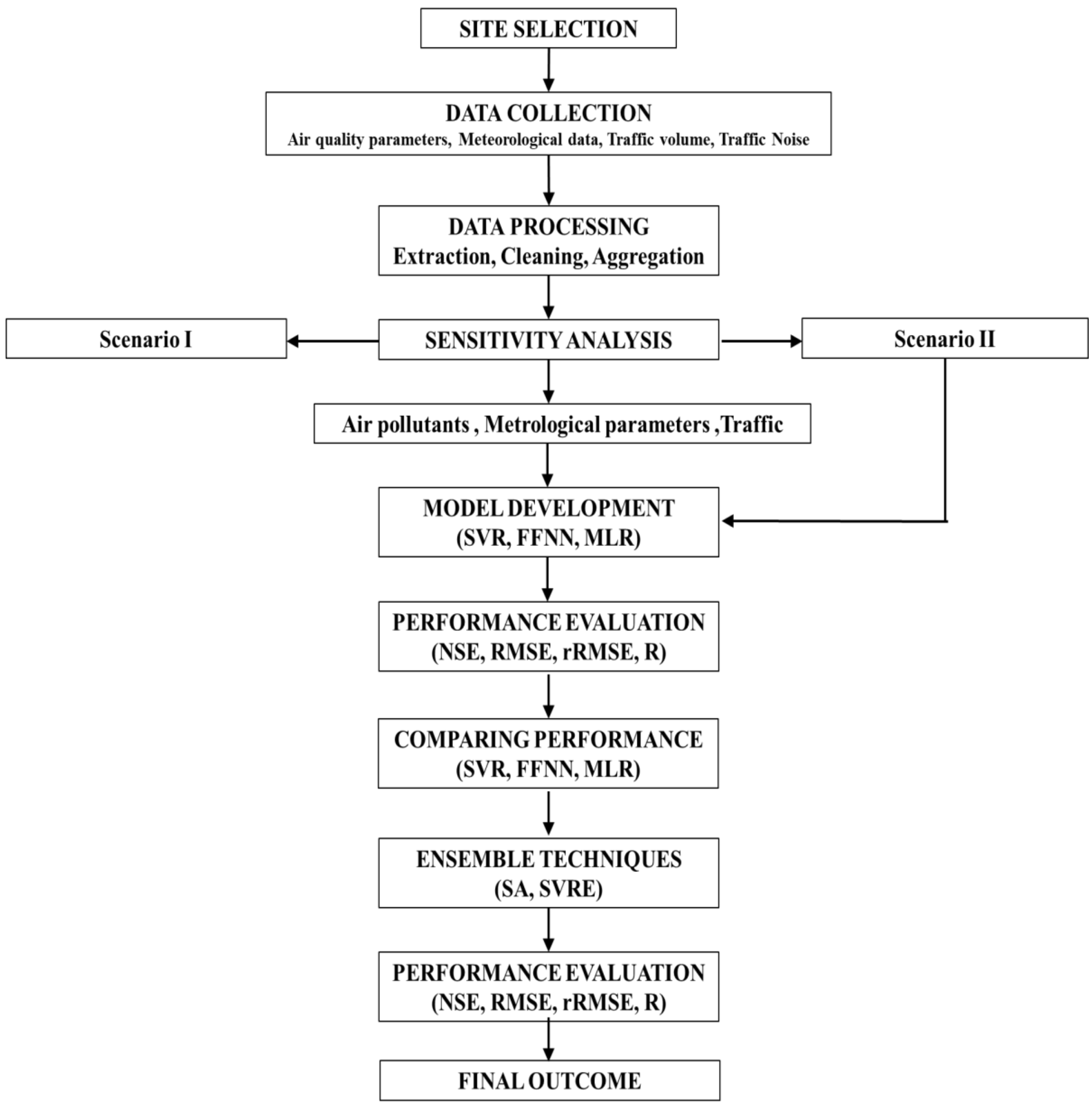
Phase II methodology

In the second phase of the study, the interaction between traffic noise and $Pm_{2.5}$ and the effect of traffic noise in predicting the $PM_{2.5}$ was studied and evaluated. To determine the interaction between the two urban pollutants and proposed methodology to predict the PM2.5 using the traffic noise as input parameter was developed.

The proposed methodology involves four main stages, the first stage involves data collection and processing. In the second stage, SVR based group sensitivity analysis was performed to identify the relevance of each of three categories of input parameters (i.e., pollutants, meteorological and traffic) in the prediction of the traffic noise, in the third stage $PM_{2.5}$ was modelled using all the three inputs group combined together for scenario I and II. In scenario I, the $PM_{2.5}$ was modelled using different input variables without traffic noise as input parameter while in scenario II, all the models were developed with traffic noise as one of the input parameters for improved prediction accuracy. Finally, an SVR based ensemble model was developed using the outputs from three data driven model (FFNN, SVR, MLR). The schematic chart of the methodology is presented in Figure 5.

Figure 5

Schematic diagram of the proposed methodology



Air and traffic noise pollution data

For conducting the study, data from 7 different data collection points in North Cyprus (Figure 6) were collected in January 2020 from 9am to 7pm. The parameters measured at each of the data collection points includes air pollutants concentration (CO_2, CO, NO_2, SO_2, $PM_{2.5}$, PM_{10}), meteorological parameters (wind direction, atmospheric pressure, relative humidity, temperature and wind speed), traffic data (cars, trucks, buses, and medium vehicles) and equivalent noise level. The air pollutants and mereological parameters were measured using the HIM600 HAZ-SCANNER having up to 12 sensors. The HAZ-SCANNER was placed on flat surface at 1m height at each of the data collection points which are located along the roadside (see Figure 7). Simultaneously with the air pollutants, 15 minutes equivalent continuous noise level was recorded using the class II sound level meter (SLM) placed at a height of 1.2m and a distance of 3m from the pavement edge. The traffic data was obtained by video recording the traffic flow at the data collection points. A total of 75 observations were recorded and each observation is measured for 15min. The traffic noise data in the study area during the peak hours ranges from 58 to 80.1 dBA. The statistical summary of the data is given in Table 1.

Figure 6

Data collection points for phase II

Figure 7

Data collection-setting up HAZ-SCANNER at point 6

Table 1

Descriptive statistics of the data

Parameters	Mean	Standard Deviation	Minimum	Maximum
RH (%)	41.22	7.87	31.00	60.60
Temp (oC)	15.33	1.17	13.80	17.40
Wind direction (deg)	151.47	92.34	36.00	356.40
Wind speed (kph)	2.62	2.05	0.00	6.62
No. Traffic volume	122	29.54	57.00	191.00
No. cars	112	29.14	50.00	178.00
No. Bus	3.27	2.96	0.00	14.00
No. Medium vehicles	4.32	3.26	0.00	21.00
No. Heavy vehicles	2.00	1.95	0.00	9.00
% HV	5.00	2.95	0.00	14.47
CO2 (ppm)	484.62	9.56	467.40	504.00
CO (ppm)	0.03	0.05	0.00	0.22
NO2 (ppb)	6.25	6.65	2.00	25.00
SO2 (ppb)	198.79	130.35	0.00	574.00
PM10 (ug/m3)	79.61	70.10	4.00	255.00
Noise	70.28	4.53	58.70	80.10
PM2.5(ug/m3	30.28	23.03	2.00	106.00

Pearson correlation

A Pearson correlation is a number between -1 and 1 that indicates how strongly two variables are linked linearly. Assume the data is a n x m matrix, with n indicating the number of instances and m indicating the number of attributes connected with each instance. Assume that X and Y are instances with m properties. The Pearson correlation coefficient, r (X,Y), between two instances X and Y is determined mathematically as:

$$r_{X,Y} = \frac{\sum_{i=1}^{m}(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{m}(X_i - \bar{X})^2}\sqrt{\sum_{i=1}^{m}(Y_i - \bar{Y})^2}} \qquad (1)$$

where $\bar{X}$ and $\bar{Y}$ are defined as:

$$\bar{X} = \frac{1}{m}\sum_{i=1}^{m} X_i \quad (2)$$

$$\bar{Y} = \frac{1}{m}\sum_{i=1}^{m} Y_i \quad (3)$$

The Pearson correlation coefficient is a measure of how linearly related two occurrences are. The value of varies between -1 and 1. If two instances are uncorrelated, it is closed to zero. X and Y are connected when it is positive. The greater the association, the higher the value. If the value of rx,y is negative, it means that X and Y are inversely correlated.

Sensitivity analysis

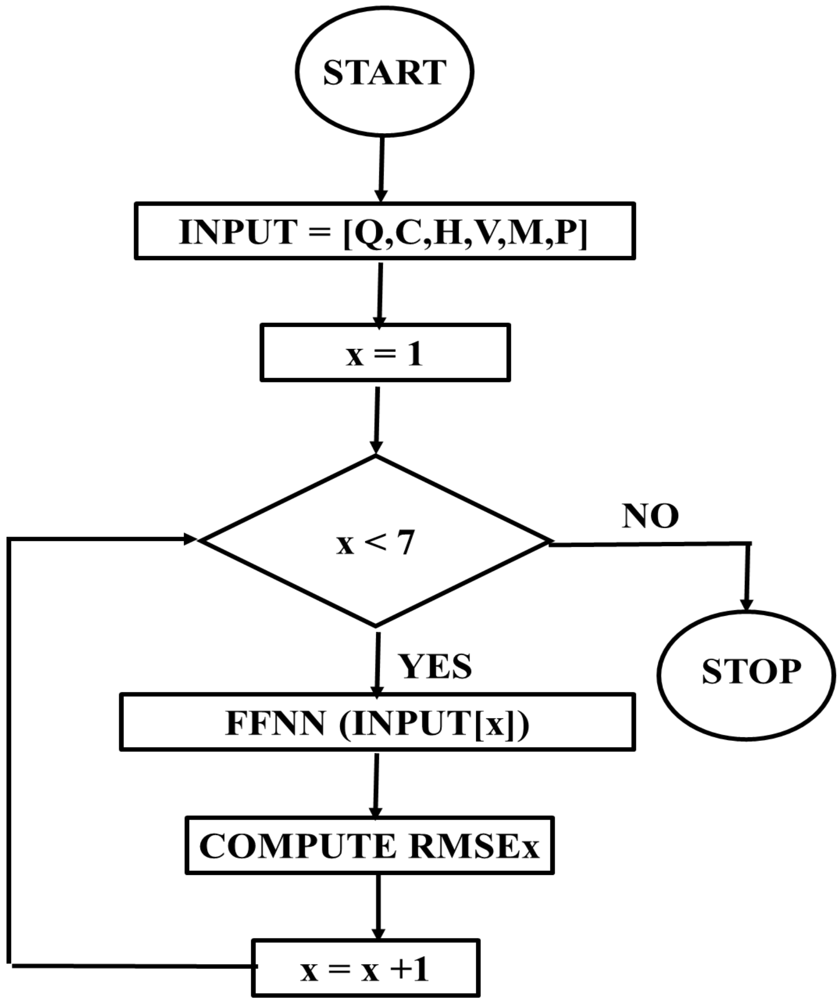
The selection of the main input parameters in AI modeling is a critical issue for achieving appropriate results. In that regard, a nonlinear sensitivity analysis was conducted in the study to determine the importance and rank of the traffic noise predictors (C, MV, HV, Q, P and V) in modeling the road traffic noise level. It was also used to determine the nature of the relationship between the input parameters and the noise in the study area. The procedures for the AI-based sensitivity analysis were explained in the following subsections.

Single input single output

In the single-input single-output neural network-based sensitivity analysis, each input parameter was imposed independently into an FFNN model to predict the road traffic noise level. By doing that, the actual relationship between the parameter and the traffic noise level was determined without considering the influence of the other potential input variables. The models' performances (RMSE) were evaluated and the RMSE values of the models in the verification stage were used to rank the relative importance of the input parameters. The parameter with the lowest RMSE value was considered to be the most important input and the importance decreases as the error value increases. The schematic of the procedure is given in Figure 8.

Figure 8

Flow chart of the single-input single- output sensitivity analysis

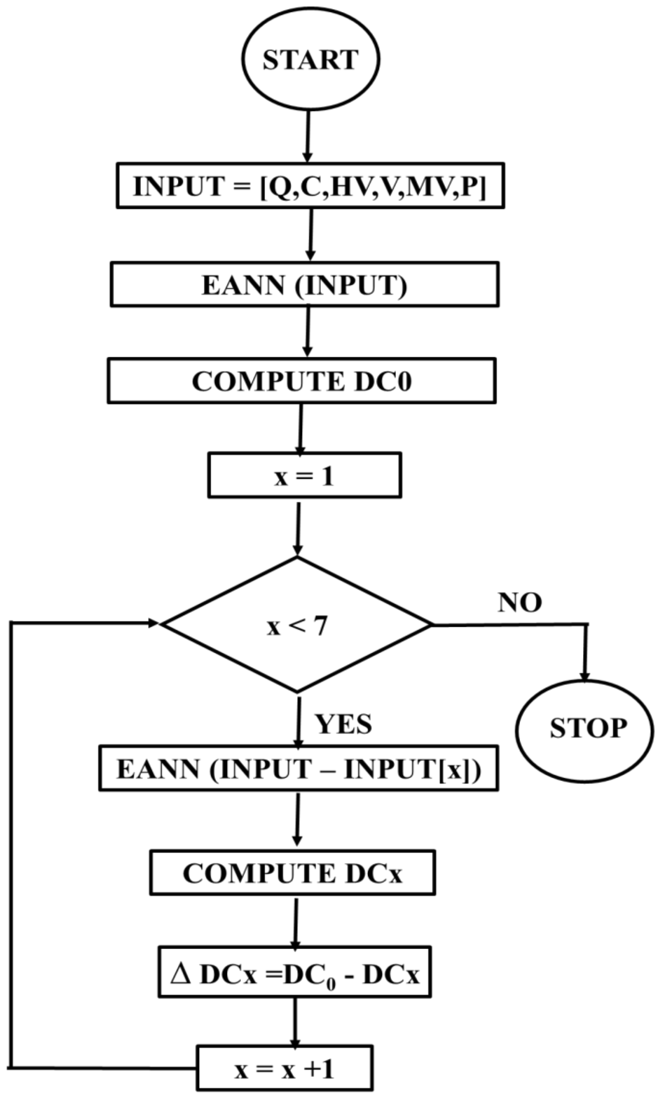


Feature removal sensitivity analysis

A feature removal sensitivity analysis using the EANN model was also used to determine the relative importance of the input parameters. The procedure for the EANN-based feature removal sensitivity analysis involved four steps (see Figure 9). In the first step, the EANN model was trained and tested using all the 6 potential input parameters (Q, C, MV, HV, V, P) as input parameter to predict the level of roadway traffic noise. Secondly, the performance (DC) of the model was computed. In the third step, one parameter (e.g. Q) was removed from the already trained and tested model, and the new model was trained and tested without that parameter (Q) and the corresponding DC value was computed. Lastly, the corresponding decrease in the DC value following the removal of the parameter Q at the testing stage was obtained and used to rank the relative importance of the parameter. The procedure was repeated for all the parameters. A higher reduction in the DC values indicates higher relative importance, while a lower reduction indicates less importance.

Figure 9

Flow chart of the EANN based feature removal sensitivity analysis



Mutual information

The MI method, on the other hand, quantifies the dependency between two random variables (Yang et al., 2000). MI can quantify the statistical non-linear dependency between two random variables and it is zero when the two random variables are independent (Nourani et al. 2015). MI between two random variables *m* and *n* can be calculated as (Yang et al., 2000):

$$MI\,(m, n) = H(m) + H(n) - H(m, n) \qquad (4)$$

where H(m) is the entropy function of m and H(m, n) is the joint entropy function of variables m and n given as:

$$E(n,m) = -\sum_{m\epsilon M}\sum_{n\epsilon N} p_{MN}\,(m,n)\,\log p_{MN}\,(m,n) \qquad (5)$$

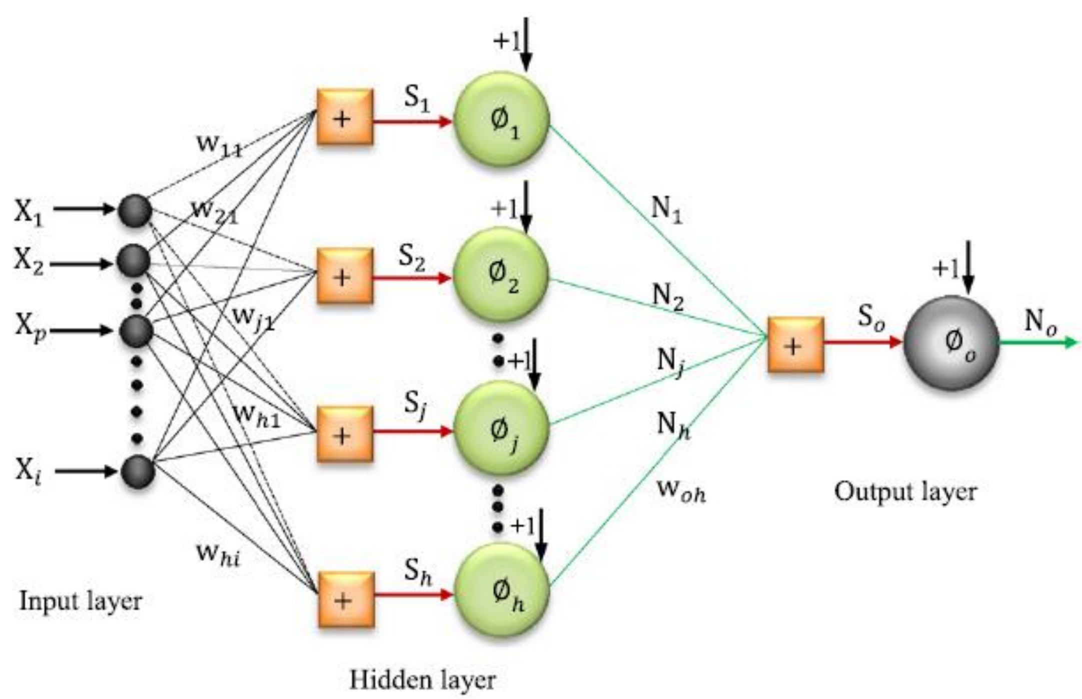
Artificial intelligence methods

Feed forward neural network (FFNN)

ANN is a computational model with an outstanding structure and functional aspect of the biological neural network. The ability of the neural network model to learn by samples makes it more robust and applicable in almost all aspects of engineering, economics, science, mathematics, neurobiology, etc. (Kumar et al., 2014). Many forms of neural networks exist and the most commonly used due to its simplicity is the FFNN trained with back-propagation (BP) algorithm (Rumelhart et al., 1986). The FFNN consists of interconnected artificial neurons called nodes with multiple layers, one for input, and at least one for the hidden layer and one for the output layer. The structure of a FFNN is shown in Figure 10. The nodes are the basic processing units of the neural network (Kumar et al., 2014). The inputs are multiplied with an adjusted weight and passed through a transfer function to provide output for that neuron (Ghaffari et al. 2006). A sigmoid function which is the most commonly used transfer function then acts on the weighted sum of the neuron’s inputs. By iterative adjustment of the weights, the neural network establishes a relationship with the input data. The ability of the neural network to establish a relationship by learning from samples makes it suitable for systems where there is no identifiable relationship between the input and output data (Genaro et al., 2010). The FFNN gets its name from its behavior of propagating information feedforward. Levenberg-Marquardt has been proposed by second-order modification of the BP algorithm which uses mainly gradient steepest descent method for training to overcome the weakness of the BP. The Levenberg-Marquardt algorithm optimizes the weights during the training by combining the steepest descent method's stability with the Gauss-Newton algorithm's speed advantage. The optimum number of hidden neurons is chosen for the neurons number with the least mean square error between the observed and the predicted data after various trials (Kumar et al., 2014).

Figure 10

A three layered FFNN

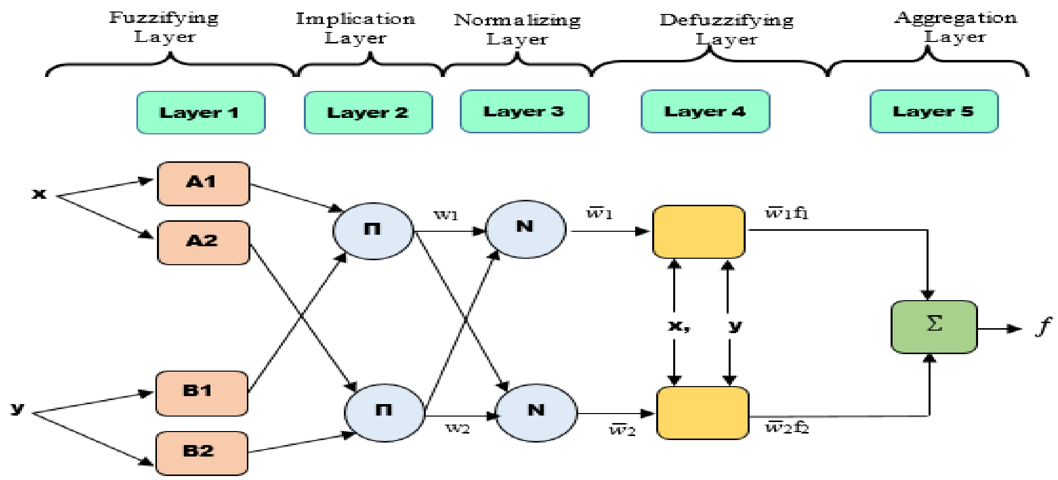


Adaptive neuro fuzzy inference system (ANFIS)

ANFIS is a useful neural network approach for the solution of function approximation problems combining the adaptive neural network and fuzzy inference system. It is a universal approximator developed by Jang (1993) to overcome the shortcomings of both ANN and FIS. ANFIS combines the learning ability of neural network and advantages of the rule-based fuzzy system that can incorporate past observations into classification process. The system is built by fuzzy logic definitions and the neural network is used to tune the system parameters automatically hence eliminating the need for manual optimization of the fuzzy system parameters unlike in neural network where the system is built by training (Rai et al. 2015). Adaptive capability and flexibility of ANFIS make it good in dealing with the uncertainty of processes, in addition to its ability in handling large noisy data from systems that are complex and dynamic (Çaydaş et al. 2009). The ANFIS model architecture consists of five layers configured like any multi-layer FFNN and named according to their operative function as illustrated in Figure 4. Sugeno first-order fuzzy model was used in the current study. Unlike the neural network where weights are tuned, determining fuzzy language rules is required for calibrating the ANFIS model. The calibration of the membership function parameters of the ANFIS model is achieved using the BP and/or least mean square and parameters of the Takagi Sugeno fuzzy model are calibrated by the traditional least square method (Nourani et al., 2011). The overall output of the ANFIS system can be expressed as a linear combination of the consequent parameters (Çaydaş et al. 2009). The general schematic of the ANFIS model is shown in Figure 11 for a two-input model.

Figure 11

First order type Sugeno FIS and ANFIS model structure (Jang 1993)



Assuming FIS with two inputs and one output as '*x*' '*y*' and '*f*'', a Sugeno fuzzy first order has the following rules:

Rule (1): if μ(x) is A_1 and μ(y) is B_1; then $f_1 = p_1x + q_1y + r_1$ (6)

Rule (2): if μ(x) is A_2 and μ(y) is B_2; then $f_2 = p_2x + q_2y + r_2$ (7)

Membership functions parameters for *x* and *y* inputs are A_1, B_1, A_2, B_2, outlet functions' parameters of *f* are p_1, q_1, r_1, p_2, q_2, r_2, a five-layer neural network layout has the formulation and structure of ANFIS as:

Layer 1: Every node *i* is an adaptive node in this layer, which has a node function as:

$Q_i^1 = \mu_{Ai}(x)$ for $i = 1,2$ or $Q_i^1 = \mu_{Bi}(x)$ for $i = 3,4$ (8)

Where Q_i^1 for input *x* or *y* is the membership grade. Gaussian membership function was chosen in this study due to its lowest error in prediction.

Layer 2: T-Norm operator connects every rule in this layer between inputs 'AND' operator as:

$Q_i^2 = w_i = \mu_{Ai}(x).\ \mu_{Bi}(y)$ for $i = 1,2$ (9)

Layer 3: ''Normalized firing strength'' is the output in this layer:

$$Q_i^3 = \overline{w} = \frac{w_i}{w_1+w_2} \qquad i = 1,2 \tag{10}$$

Layer 4: Every node *i* in this layer is an adaptive node and performs the consequent of the rules as:

$$Q_i^4 = (p_i x + q_i y + r_i) = \overline{w} f_i \tag{11}$$

represents the output of layer 3 and , , are the consequent parameters.

Layer 5: The overall output of all incoming signals is computed in this layer as:

$$Q_i^5 = (p_i x + q_i y + r_i) = \quad \Sigma w_i f_i = \frac{\Sigma w_i f_i}{\Sigma w_i} \tag{12}$$

Support vector regression (SVR)

SVR is a regression method used for modelling the complex and nonlinear processes which is developed on the basis of support vector machine (SVM) concept. Like other SVM based methods, minimizing the operational risk is the major objective of the SVR which is different from other black box models where the main objective is minimizing error between measured and predicted values. The SVR involved two stages, at first the data are fitted into a linear regression, then the output passes through a nonlinear kernel which takes the nonlinear form of the data. Given a set of training data $\{(x_i, d_i)\}_i^N$ (where x_i, d_i and N represents input vector, actual value and total number of data patterns). The general expression of the SVR function can be written as (Wang et al., 2015):

$$y = f(x) = \omega\varphi\,(x_i) + b \tag{13}$$

where ω, $\varphi(x_i)$, x and b represent m-dimensional weight vector, feature spaces, non-linearly mapped from input vector and the bias, respectively (Vapnik 1998) .Parameters b and w can be computed by giving positive values for the slack parameters of ξ and ξ^* and minimization of the objective function as (Wang et al., 2015):

$$\text{Minimize:} \qquad \frac{1}{2} \parallel w \parallel^2 + C\left[\sum_i^N (\xi_i + \xi_i^*)\right] \tag{14}$$

Subject to: $\begin{cases} w_i\varphi(x_i) + b_i - d_i \leq \varepsilon + \xi_i^* \\ d_i - w_i\varphi(x_i) + b_i \leq \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* \end{cases}$ i=1,2,…,N

Where $\frac{1}{2} \parallel w \parallel^2$ is the weights vector norm, C is the regularized constant that sets the tradeoff between the empirical error and the regularized term, and is the tube size that correlates to the approximation accuracy inside the training data points. By establishing Lagrange multipliers α_i and α_i*, the preceding optimization problem may be transformed into a dual quadratic optimization problem. By solving the quadratic optimization problem as follows, the vector *w* may be computed as (Wang et al., 2015):

$$w^* = \sum_{i=1}^{N}(\alpha_i - \alpha_i^*)\varphi(x_i) \tag{15}$$

The final expression of the SVR can be written as (Wang et al., 2015):

$$f(x, \alpha_i, \alpha_i^*) = \sum_{i=1}^{N}(\alpha_i - \alpha_i^*)K(x, x_i) + b \tag{16}$$

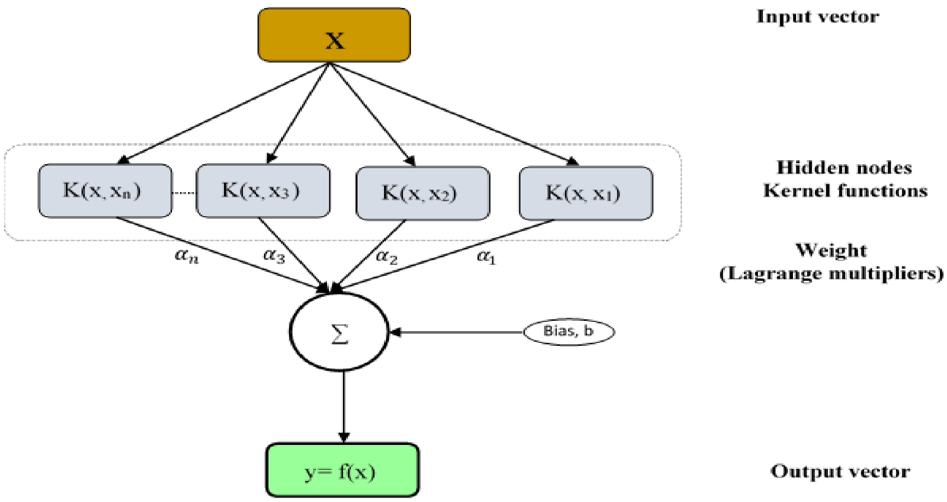
$k(x_i, x_j)$ is the kernel function performing the non-linear mapping into feature space and *b* is bias term. One commonly used kernel function is the Gaussian Radial Basis Function (RBF) kernel as:

$$k(x_1, x_2) = \exp(-\gamma\|x_1 - x_2\|^2) \tag{17}$$

where, γ is the kernel parameter. The general conceptual structure of the SVR is presented in Figure 12.

Figure 12

Conceptual architecture of SVM algorithm



Multi linear regression

In engineering sciences, linear regression analysis is a typical approach for modeling and analyzing many variables. Regression analysis is particularly useful for understanding how the typical value of the dependent variable changes when one or more of the independent variables is changed while the other independent variables remain constant, as well as for exploring the interactions that describe the relationship between these variables(Doğan and Akgüngör 2013). The dependent variable, and regressor variables may be related by (Elkiran et al., 2018):

$$y = b_0 + b_1x_1 + b_2x_2 + b_3x_3 + \cdots + b_ix_i + \xi \tag{18}$$

Where x_i is the value of the i^{th} predictor, b_0 is the regression constant, b_i is the coefficient of the i^{th} predictor and ξ is the error term.

Gaussian Process Regression (GPR)

Gaussian Process Regression (GPR) is a non-parametric technique that is used to model random complex systems. The flexibility of the GPR method in providing uncertainty representation makes it more desirable in the prediction of many engineering problems (Rasmussen 2004). The GP is a stochastic process of which finite sub-collection of random variables has a multivariate Gaussian distribution (Cai et al. 2020). The general expression of the GPR model relating the explanatory vector (*x*) and the response (*y*) is given by:

$$y_i = f(x_i) + \varepsilon \tag{19}$$

In Equation 6, $f(x_i)$ stands for an arbitrary function that maps the inputs into the corresponding outputs, ε represents the regression error having an identically distributed Gaussian function with mean and variance values of zero and σ^2, respectively.

The function *f(x)* for any unobserved pair *(x*, f*)* in which *f* is the response and *x* is the explanatory parameter is obtained by:

$$\begin{bmatrix} f \\ f^* \end{bmatrix} \sim \mathrm{N}_{n+1}\left(0, \begin{bmatrix} K(X,X) & k(X,x^*) \\ k(x^*,X) & k(x^*,x^*) \end{bmatrix}\right) \tag{20}$$

In Equation 7, *K (X, X)* represents the matrix of covariances (*n* x *n*) for all samples in the calibration data, *k* (X, x*) stands for vector of covariances ($n \times 1$) between the point *x** and calibration data. *k(x*, x*)* is the variance at point *x**. In the classic regression, the mean (*f*) is derived from *f* then integrates to *f**:

$$P(f * | x *, X, f)$$
$$= N|(\, k(x *, X)K(X,X)^{-1}\, f, k(x *, x *) - k(x *, X)K(X,X)^{-1}\, k(X, x$$
$$*))$$

(21)

Equation (21) expresses X and *f* by maximizing the joint probability of *f** conditional on *x** to obtain the *f**.

When using data that is noisy, it should be supplemented by a model for the observation error. Hence, Equation (20) is converted into:

$$\begin{bmatrix} f \\ f^* \end{bmatrix} \sim \mathrm{N}_{n+1}\left(0, \begin{bmatrix} K(X,X) + \sigma^2\mathrm{I} & k(X,x^*) \\ k(x^*,X) & k(x^*,x^*) \end{bmatrix}\right) \tag{22}$$

consequently, the conditional likelihood and the variance change to

$$f(\, x^*,) = k\,(\, x^*,\; X)\,(K\,(X,X) + \;\sigma^2\, I)^{-1} f \tag{23}$$

and

$$Cov\,(f(\,x^*)) \;=\; k\,(\,x^*,\,x^*) - \;k\,(\,x^*,X)\,(K\,(X,X)\;+\;\sigma^2\,I) - \;k\,(x,\,x^*) \qquad (24)$$

where I stands for identity matrix and σ^2 represents variance of the measured error (Bonakdari et al. 2019).

Boosted Regression Tree (BRT)

The BRT is a unique method for prediction and classification combining both a machine learning approach and a statistical technique. The BRT combines several models and fit them into single model for improving performance of the single models in prediction problems (Youssef et al. 2016). The method does not require any data transformation before fitting the complex nonlinear pattern of the dataset and establishing the interaction between the target and input variables (Elith et al. 2008). This advantage of the BRT makes it suitable for modelling natural processes with complex nonlinear relationships. Information in decision trees is represented in distinctive way that is easy to visualize which gives it several advantages. In the BRT, missing data in the predictor variables are modified using surrogates (Elith et al. 2008). Another advantage of all decision trees including the BRT is their insensitivity to outliers. Boosting and regression are the two algorithms used in the BRT models. Boosting is a technique used for enhancing prediction accuracy of a model based on the idea that, it is easier to find many rough rules of thumb than to find a single and highly accurate prediction rule (Youssef et al. 2016). Fitting multiple regression trees in the BRT overcomes the deficiency of the single regression trees in predictions. The Regression Learner of Matlab (2019b) was employed for developing the BRT model in this study. For a typical predictive learning system consisting of a set of predictors of different variables X= $\{x_1\ldots, x_n\}$ and a response variable y, a BRT for function approximation could be applied. For example, using a training sample $\{y_i, X_i\}$, i =1…, N of known y and X values. The aim is to determine the function F^*(X) (Equation 12) that fits X to y, such that the anticipated value of the identified loss function is minimized over the joint distribution of all values of X and y. In gradient boosting regression, the function is approximated using Equation 26.

$$F^*\,(X) = \psi\,(y, F(X)) \qquad (25)$$

$$F(X) = \sum_{m=0}^{M} F_m(X) = \sum_{m=0}^{M} \beta_m g(X; \alpha_m) \tag{26}$$

Where g (X; α_m) stands for the regression tree at a specific node, β_m are the expansion coefficients, αm explains the tree parameters, m=1…, M. The X space is divided into N-disjointed regions {R_{nm}} for each iteration m, n=1…, N and distinct constant are estimated in each iteration (Suleiman et al. 2016). The following steps are employed for implementing the BRT algorithm:

1. Initialize F(X) to be a constant
2. Do the following steps for values of m from 1 to M:
   a. Compute the residual error $r = -\left[\partial\psi y_i, \frac{F(X_i)}{\partial F(X_i)}\right] F_m(X) = F_{m-1}(X), i = 1, \dots, N$
   b. Without replacement, select randomly p ×N samples from the calibration data.
   c. To obtain the approximate α_m value of $\beta g(X; \alpha)$, fit the r values computed is step 2a into a least squares regression trees with K terminal nodes using the randomly selected observations in 2b.
   d. Minimize the loss function $\psi\big(y, Fm - 1(X)\big) + \beta g(X; \alpha_m)$ to obtain the approximate values of β_m.
   e. Update $F_m(X) = F_{m-1}(X) + \beta_{mg}(X; \alpha_m)$
3. Calculate $F_m(X) = \sum_{m=0}^{M} F_m(X)$

For the avoidance of overfitting problems expected in the BRT models, a learning rate λ parameter that controls the contribution of each regression tree is added to keep the condition under control by moderating the calibration process of the regression trees as shown in Equation 27. There is a strong interaction between λ and number of iterations M. For convergence of the calibration error, more iterations are required for smaller values of *m*. Setting the λ to a small constant value and choosing fewer number of iterations has been recommended by Hastie et al., (2011) for obtaining better test error.

$$F_m(X) = F_{m-1}(X) + \lambda\beta_{mg}(X; \alpha_m) \tag{27}$$

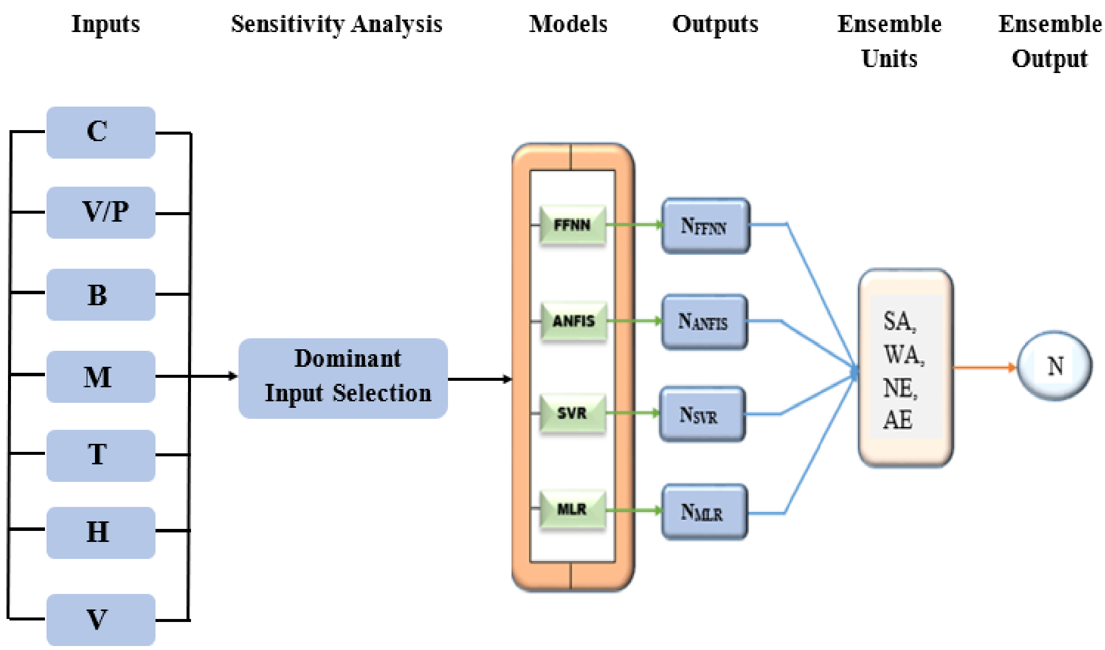
Ensemble techniques

The ensemble approach is a machine learning technique that combines the results of numerous predictors to improve overall performance (Sharghi et al. 2018). According to Raj & Ravi (2008), there are two types of ensemble methods: (1) linear ensemble through simple averaging, weighted averaging, and weighted median; and (2) nonlinear ensemble approach, in which an ANN is trained as a nonlinear kernel to provide an ensemble output. Other nonlinear kernels, such as ANFIS, SVM, and so on, can be used instead for a nonlinear ensemble (Nourani, et al., 2018a). The goal of creating ensemble models is to get the following advantages: i) It can be difficult to choose an acceptable model for modeling a specific time series problem; however, using an ensemble method eliminates this challenge since nonlinear ensemble models can produce results that are even better than the best base models (Nourani et al. 2020a) ii) In some real-world processes with both linear and nonlinear features, neither linear nor nonlinear models can accurately forecast the outcome since mistakes in the linear pattern might be inherited and increased by nonlinear models, and vice versa. The linear and nonlinear patterns in the data might be efficiently captured by integrating the outputs of linear models (MLR) with nonlinear models (ANN, SVR, ANFIS), the linear and the nonlinear patterns in the data could be captured effectively (Nourani et al. 2019a) iii) According to Sharghi et al. (2018), there is no one model that can perfectly study a certain process. That's because real-world circumstances are multifaceted, and one model may not be able to understand the numerous patterns associated with a particular process. This is owing to the complicated structure of real-world situations, which makes it unlikely that a single model would be able to distinguish between multiple patterns of a certain procedure.

Application of ensemble techniques in several fields of engineering such as web ranking, classification and clustering, time series and regression modeling proved to provide better results than single models (Nourani, et al., 2018b; Nourani, et al., 2019b). Four ensemble techniques (2-linear and 2-non-linear) were employed in this study to increase accuracy of the single models in the prediction of vehicular traffic noise. The general structure of the ensemble technique is presented in Figure 13.

Figure 13

General procedure of developed ensemble technique



Linear ensembles

a. In the simple average (SA) ensemble, the arithmetic average of the outputs (noise level) of the FFNN, ANFIS, SVM and MLR models is taken as the predicted noise value as:

$$\bar{N} = \frac{1}{N} \sum_{i=1}^{n_m} N_i \qquad (28)$$

In which $\bar{N}$ shows the outcome of simple average ensemble method (noise level), n_m is the number of used models (in this study, n_m =4) and N_i stands for the outcome of the i^{th} method (i.e., ANN, ANFIS, SVR and MLR).

b. Weighted averaging (WA) ensemble, weighted average of the noise level is computed by giving distinct weights to the outputs of the single models based on their relative importance. The weight is assigned based on relative significance (DC value) of the output. The WA is expressed by:

$$\bar{N} = \sum_{i=1}^{n_m} w_i \, N_i \tag{29}$$

where w_i is the applied weight on the output of the i^{th} model which can be determined based on the model performance obtained by:

$$w_i = \frac{DC_i}{\sum_i^{n_m} DC_i} \tag{30}$$

DC_i is the performance efficiency of the i^{th} single model.

Non-linear averaging ensemble

In the nonlinear ensemble techniques, AI-based models (FFNN and ANFIS) are trained to perform non-linear averaging of the noise levels obtained from the single models. The input layer of the ensemble technique is fed by the outputs of the considered models, each considered as one input variable.

c. For the non-linear neural ensemble (NE) technique another FFNN model is trained by feeding the outputs of Single models as inputs to the neurons of the input layer. The number of hidden layer neurons and maximum epoch numbers are defined through trial-error.

d. For the ANFIS ensemble (AE), outputs of Single models are fed to an ANFIS to be trained using different membership functions and epochs.

Hybrid Modelling

In many real-life problems such as the roadway traffic noise prediction, a linear or a nonlinear interaction may exist between the predictor variables and the roadway traffic noise level. As a result of this complex nature, the application of linear models (such as MLR, ARIMA) for such process may not be adequate. On the other hand, nonlinear models (such as ANN, SVR etc.) despite their advantage in modelling complex problems are not appropriate for all circumstances and may yield errors especially in modelling data with a linear pattern. Therefore, it is not appropriate to blindly apply nonlinear models to any data without pre-processing of the data. For example, a spatial data pre-processing (e.g. spatial clustering) should be employed for modelling processes that shows trend in space before developing main models. Likewise, temporal data pre-processing may improve the model efficiency for processes which include seasonal and non-stationary characteristics. Because it is difficult to fully comprehend the properties of data in a real-world scenario, hybrid modeling can be a useful tool for capturing different parts of the underlying patterns by combining several models (Nourani et al., 2011). In this study, a hybrid model was developed by combining the predicted values from a linear model (MLR) and estimated residuals (error) by a nonlinear model (AI-based). The proposed hybrid model can be expressed as:

$$y_i = L_i + N_i, \tag{31}$$

Where y_i is the observed noise level; L_i and N_i are the linear and nonlinear parts of the traffic noise, respectively. The development of the proposed linear-nonlinear hybrid model involved three steps (Figure 14). For the first step, a linear model is created via MLR and the residuals are computed using:

$$r_i = N_{obs(i)} - N_{pre(i)}. \tag{32}$$

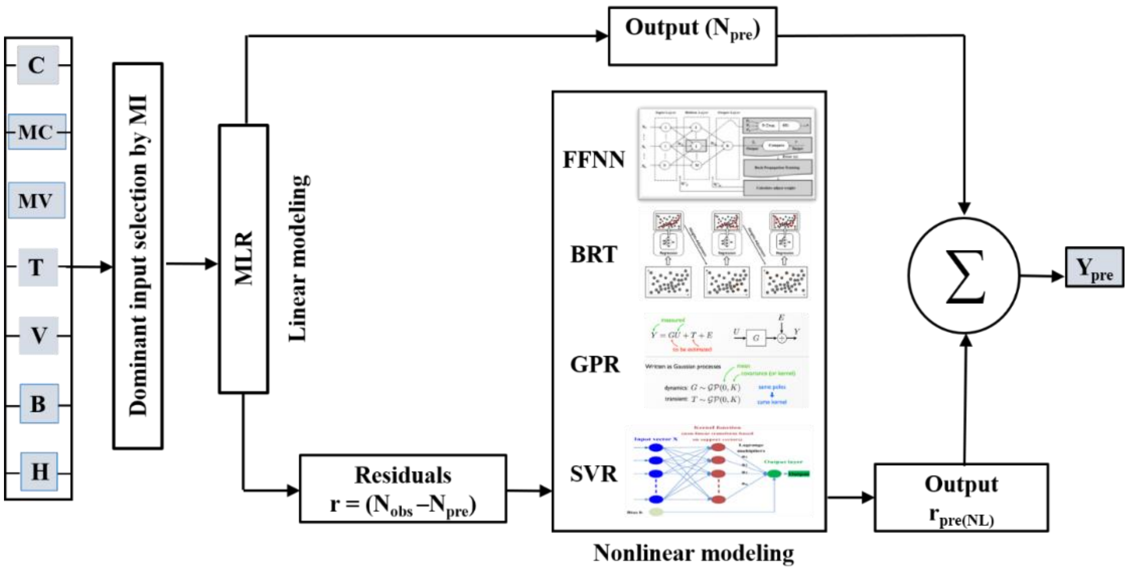
Where the residual r_i is estimated by the MLR models, $N_{obs(i)}$ and $N_{pre(i)}$ present the observed noise level, and predicted noise level by MLR model, respectively. In the second stage, the residual (r_i) which contains only the nonlinear part of the traffic noise that was not captured by the MLR, is passed through a nonlinear kernel of AI model, (e.g. FFNN, SVR, BRT and GPR) for capturing the nonlinearity of the data. Lastly in step three, the result obtained from the nonlinear model is combined (summed up) with the output of the MLR model obtained in step 1 to give the predicted noise level by the hybrid model. The final traffic noise computed by the hybrid model is given by Equation 3.33. By combining the MLR and AI-based models in roadway traffic noise prediction, the MLR will effectively capture the linear pattern in the data and the AI-based models will capture the nonlinearity of the data there by coming up with a model that has higher prediction accuracy than both MLR and the AI-based models as hinted by Nourani et al., (2011).

$$Y_{pre} = N_{pre} + r_{pre} \tag{33}$$

Where Y_{pre} is the predicted noise level, N_{pre} stands for the approximated noise level obtained by MLR and r_{pre} is the predicted residual obtained using the AI model.

Figure 14

Proposed linear-nonlinear hybrid model



Emotional Artificial Neural Network (EANN)

Recently, the integration of the emotions into ANN to form the EANN is getting attention of the scientists. From the biological point of view, the neurophysiological response of an animal to a certain task under different disposition is determined by its emotions due the activity of the hormone glands. In the EANN, the learning ability of the model is improved by providing a feedback loop to link the hormonal and neural system in a way that each node is affected by the other. The mathematical development and application of the EANN is still in its primary stage. Some EANN training algorithms developed over the past few years for modelling complex engineering problems includes the brain emotional learning (BEL), emotional backpropagation algorithms (EmBP) and limbic-based artificial emotional neural network (LiAENN), each having its distinct features and advantages. The BEL algorithm was proposed by Moren (2002), the inspiration of developing the BEL learning algorithm was derived from biological proof indicating faster response by animals exposed to emotional stimulus (e.g. terror, fear) when only limited time is available for processing external conditions like danger through shorter path in the brain. Similarly, with integration of hormones into the BEL, the convergence period of the model in obtaining satisfactory result is minimized by processing information through shorter paths in the network. The EmBP algorithm which is a simplified EANN was proposed by Khashman, (2008) where anxiety and confidence were employed for attuning parameters of the backpropagation neural network. In the EmBP, the coefficients of anxiety are first initialized depending upon the pattern of the training data. The anxiety factors are then adjusted during the calibration of the model. The anxiety factors are set high at the initial stage of the network calibration, while confidence level is set low but once some few iterations were completed, optimal values for the anxiety and the confidence are obtained. Positive feedbacks make the anxiety to decrease, and as the anxiety level decreases the confidence level increases. setting the anxiety level high at the initial training stage of the model forces the network to give less priority to the error gradient in the output of the network. The rise in the confidence level on the other hand makes the network to give consideration in adjusting the weights in the preceding iteration. The LiAENN algorithm on the other hand combined some features and advantages of both the BEL and the EmBP algorithms by incorporating both emotional states and anatomical bases of emotion. It is employed for multiple input/output pattern classification, pattern recognition and prediction problems. In the LiAENN, attuning weights of the training algorithm is done by anxious confident decayed brain emotional learning (ACDBEL) rules. Confidence and anxiety are the emotional situations used in the LiAENN while inhibitory task of orbitofrontal cortex, vague and fast routes in the emotional brain, and forgetting process of amygdala are the anatomical features utilized for architecture of the LiAENN algorithm. The LiAENN was found to perform better than both BEL in EmBP for facial recognition (Lotfi and Akbarzadeh-T., 2014).

EANN models are the advanced inventions of the traditional FFNN models, integrating an artificial emotion system capable of radiating emotional hormones to acclimatize the performance of all network nodes. In the feedback loop, the hormonal weights are adjusted based on the values in the input and the response nodes. All the nodes in the EANN model are capable of sending and receiving signals reversibly between the input and the output nodes to produce dynamical hormones (e.g. Ha, Hb and Hc). At initiation, the coefficients of the dynamic hormones are randomly chosen depending on the data pattern which are fine-tuned during the training phase after few iterations. All the neuron components (activation function, net function and weight) are affected by the hormonal coefficients. In the EANN structure (Figure 15), the dotted line represents the hormonal paths while the paths for neural information are represented by the solid lines. With three hormonal glands Ha; Hb and Hc of the EANN The output of i^th^ neuron in can be calculated using:

$$\Bigg(\underbrace{\gamma_i + \sum_h \partial_{i,h} H_h)}_{1} \text{ x } f(\sum_j [\underbrace{(\beta_i + \sum_h \chi_{i,h}\, H_h)}_{2} \text{ x } (\underbrace{\alpha_{i,j} + \sum_h \Phi_{i,j,k}\, H_h) X_{i,j}}_{3} +$$

$$[\underbrace{(\mu_i + \sum_h \Psi_{i,h}\, H_h)]}_{4}\Bigg) \qquad (34)$$

where i, h, and j represent the neurons of the input, hidden and output layers and *f ()* symbolize an activation function. The artificial hormones are calculated as (Nourani 2017):

$$H_h = \sum_i H_{i,h}\ (h = a, b, c) \qquad (35)$$

In Equation 34, expression (1) signifies the required weight of the activation function (*f*). It incorporates the statistic weight γ_i of the neural network along with the weight of $\sum_h \partial_{i,h} H_h$ of dynamic hormones. Expression (2) indicates the weight applied to the net function, Expression (3) stands for the weight applied to $X_{i,j}$ input from j^th^ node of previous layer and Expression (4) stands for the bias of the total functions, comprising of hormonal weights $\sum_h \Psi_{i,h}\, H_h$, and the neural weights μ_iy. The sharing of the whole hormonal values of EANN (i.e., H_h) amongst the hormones should be regulated by ∂_i, h, χ_i, h, $\Phi_{i,j,k}$ and $\psi_{i,h}$ features and consequently, the i^th^ node output (Y_i) will give hormonal response of $H_{i,h}$ to the network as (Nourani 2017):

$$H_{i,h} = glandity_{\ i,h} \times Y_i \qquad (36)$$

In order to give a sufficient hormone level to the glands, the glandity factor should be adjusted during the EANN training phase. Certain approaches, such as the average of the input vector of learning samples, could be utilized to adjust the hormonal levels of Hh depending on the input data. Following that, the hormonal values are recalculated using the network output (Yi) and Equations.35 and 36 to get a fitting value between the estimated and observed vehicular traffic noise level. EmBP algorithm was used to train the network in this study, the EmBP combine the learning parameters (learning factor (η) and momentum rate (α)) of BP with the emotional parameters (anxiety coefficient (μ) and confidence coefficient (k) ($0 < \mu$ and $k < 1$)) for minimizing the computational error and the computational time. The μ values depends on the pattern in the inputs alongside the net output error in each iteration. During the training, values of μ fell and those of k grew, until the highest hormonal values of confidence and the lowest hormonal values of anxiety were achieved at the conclusion. Only feedforward calculations are conducted in network convergence, while network classification is done in the output layer. The EANN uses the same weight update procedure as the conventional BP technique. At each iteration of EmBP training process, the error value at output neuron (Δ) is propagated backward to adjust conventional weights (wjh) and bias (wjb) of the hidden layer as:

$$wjh(new) = wjh(old) + \mu.\Delta.YHh + \alpha.[\delta wjh(old)] \quad (37)$$

$$wjb(new) = wjb(old) + \mu.\Delta + \alpha.[\delta wjb(old)] \quad (38)$$

Where $\delta w_{jh}(old)$ and $\delta wjb(old)$ are the last alternated weight and bias values, respectively while YH_h is the h^{th} hidden neuron output. The emotional weight (w_{jm}) is updated as:

$$wjm(new) = wjm(old) + \mu.\Delta.Yavg + k.[\delta wjm(old)] \quad (39)$$

$\delta w_{jm}(old)$ stands for the earlier interchanged emotional weights, and Y_{avg} denotes the average input pattern value imposed on the EANN model in each iteration. In this equation, the μ and k values are expressed as Equations (40) and (41) respectively:

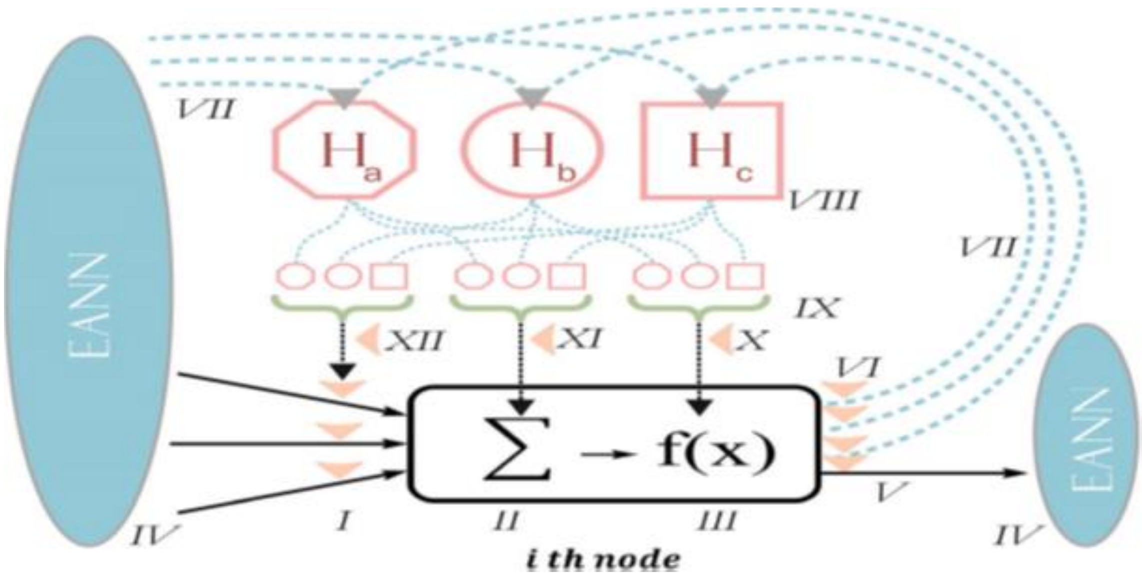
$$\mu = Yavg+\Delta \quad (40)$$

$$k = \mu 0 - \mu \quad (41)$$

Where, μ_0 is the coefficient of anxiety factor at the end of the first epoch. Adjustment of the weights and bias of input layer to hidden layer are also performed in a similar manner. For a more comprehensive details relate to the BP-based training of EANN, the author can refer to Khashman (2008).

Figure 15

A node of EANN and emotional unit



The numerical numbers I, II, III, and IV indicate the neuron elements of the input weights, net function, activation function, and output unit, respectively, in the training method of the EANN model illustrated in Figure 6, and are comparable to those of the traditional FFNN. IX, X, XI, and XII indicate the hormone net unit, hormone activation function, net function, and input static weight, respectively, while V, VI, VII, and VIII represent the net output weight, the glandity of hormone Hh, and hormones from the input or output hormonal unit.

The major difference between the FFNN and the EANN is the architecture of the models and the manner in which information is transferred between the system units. In the FFNN, the model has three units (inputs layer, hidden layer and the output layer) and signals from the inputs layer are fed forward to the hidden layer which sends the overall information to the output layer through an activation function for handling the nonlinearity in the data. The EANN as a modified form of the FFNN has an emotional system that emits emotions generated from the input data. The emotions help the network in identifying different situations during the calibration stage and consequently improves the decision-making process of the system. The possibility of overfitting in the FFNN model trained with the BP algorithm due to fewer observation data and number of parameters to be calibrated in the training face is minimized with the inclusion of the hormonal units in the EANN. The EANN model performs better due to the ability of the network to discern different circumstances of the process in the training stage. Unlike in the FFNN where information from the input to the output layer is fed only in the forward direction, information can be sent/received reversibly in the EANN (Nourani 2017). Another feature distinguishing the EANN from the FFNN is that, the elements of the feedback system modify the cells based on the hormone levels. This means that the "*Hill-function*" which acts as the "*outfunction*" in the EANN is influenced by the hormones during runtime unlike in the FFNN model where the "*outfunction*" is usually static during runtime (Thenius et al. 2013).

Empirical traffic noise models

For comparison, the result of the developed models was compared with that of the classical traffic noise models such as the RLS90, BURGESS and CNR. The RLS90 model was developed in Germany and is still the most relevant empirical model in the country. The equivalent noise level at 25m from the noise source under idealized traffic condition is expressed as the function of the traffic flow and percentage of heavy vehicles. The CNR model was developed by the Italian "Consiglio Nazionale Delle Ricerche" by modifying the German RLS90 model. In the CNR model, the traffic is categorized into subcategories taking into account their different acoustic contributions to the overall traffic noise level (Garg and Maji, 2014). The first application of the Burgess model was in Sydney, Australia. The model expresses the noise level as a function of traffic flow, distance of the source from the receiver and percentage of heavy vehicles in the traffic (Quartieri et al., 2009). The model's expressions for obtaining road traffic noise levels with the abovementioned empirical models are given by:

$$CNR: L_{eq} = 35.1 + 10log\ (+) - 10log + 1.5 \qquad (42)$$

$$RLS90: L_{eq} = 37.5 + log \qquad (43)$$

$$BURGESS: L_{eq} = 55.5 + 10.2logQ + 0.3P - 19.3log(d) \qquad (44)$$

Where Q represents the total traffic, Q_L stands for volume of light vehicles, Q_P denotes the volume of heavy vehicles, P indicates the percentage of heavy vehicles and d represents the distance of the receiver from the noise source, considered as 4m in the study.

Model Validation

The major aim of using data-driven models for prediction of complex problems is to get a dependable result that is cannot be obtained using the classical approach without erstwhile knowledge and profound knowledge of the concept. But, due to overestimation and under fitting problems in many data driven models, the performance of models at the calibration phase is not mostly coherent with its performance at the verification phase, which makes it difficult to get correct prediction results for other unseen dataset. This makes it necessary to validate the models for overcoming the overfitting issues. Despite the fact that, hybrid models handle the overfitting problems much better than the traditional feed forward neural network, because the main part of the model is MLR (linear model) which is not so sensitive to overfitting issue, it may also experience overfitting issues as a result of fewer observation samples for training the model. Various forms of validation process exist in the literature such as holdout validation and leave one out validation, cross validation, etc. but the k-fold cross validation was used for purpose of this study. In this type of validation mechanism, the dataset is portioned into equal k-number of subsets. The calibration of the model is done using k-1 subsets and remaining subset is used for the verification. The procedure is repeated for k times until all the k-subsets are used for the calibration and verification in alteration. The final performance is obtained by computing the average value of k- subsets performances in verification stage. One of the key benefit of using the k-fold cross validation is that the calibration and the verification subsets are independent (Sharma et al. 2018). Efficiency in the data usage could also be achieved through the cross validation. Considering the 4-fold cross-validation, the data set (normalized) is divided into two (calibration=75 % and validation=25 for developing the models. The data size determines the k values to be used usually ranging from 2-10.

Data pre-processing and performance evaluation

Data normalization is used to bring all the inputs and outputs variables into same range before feeding them to the AI models in order to prevent data in the lower numeric range from being overshadowed by data in the upper numeric range. (Nourani et al., 2019a). Another benefit of the data normalization is the simplification of the numerical calculations in the model which in turns increases model's accuracy and reduces the time taken to obtain the global/local minimum. In this study, the data were normalized between 0 and 1 using Equation 45:

$$N_{norm} = \frac{N - N_{min}}{N_{max} - N_{min}} \quad (45)$$

Where N_{norm} is the normalized noise value, N, N_{max} and N_{min} are the observed, highest and least values of the noise level, respectively. For model developments, the normalized data set is divided into two; 70% for calibration and 30% for verification purposes.

The efficiency of the developed models in predicting the equivalent noise level was evaluated using six different evaluation criteria namely the root mean square error (RMSE), mean absolute error (MAE), Nash-Sutcliffe efficiency (NSE) and the relative root mean square error (rRMSE). The NSE values ranges from -∞ to 1 and it is a parameter that indicates how well the model fits the observed noise level. A perfect model has an NSE value of 1 and the model efficiency decreases as the value moves far from 1 and vice versa Nourani et al., (2020a). The model's accuracy can be interpreted based on the NSE values as very good ($0.75 < NSE \leq 1$), good ($0.65 < NSE \leq 0.75$), satisfactory ($0.50 \leq NSE \leq 0.65$) and unsatisfactory ($NSE < 0.50$) (Moriasi et al. 2007). RMSE as one of the best measures for computing the model's performance was used for measuring the average error produced by the models. The RMSE value ranged between 0 and +∞ and is zero in the best model (Nourani and Sayyah 2012). The MAE construes the goodness-of-fit of the model regardless of the sign of the prediction error between observed and predicted noise level values just like RMSE. MAE was used in the study for evaluating the deviations of the predicted noise level from the observed values in an equal way regardless of the sign since the RMSE is suitable for estimating errors with a normal distribution which may not be satisfied by all proposed models (Bonakdari et al. 2019). Finally, rRMSE was also used, which could be evaluated based on the defined ranges: Excellent for rRMSE values less than 10%, Good for values between 10% and 20%, Fair for rRMSE values between 20% and 30%, and Poor if rRMSE value is greater than 30% (Rabehi et al. 2020). The closer MAE and BIAS values approach 0, the better the model's prediction. The performance evaluations mentioned are computed using Equations 46 - 51, respectively.

$$NSE/DC = 1 - \frac{\sum_{i=1}^{n}\left(N_{obs_i} - N_{pre_i}\right)^2}{\sum_{i=1}^{n}\left(N_{obs_i} - \overline{N_{pre_i}}\right)^2} \tag{46}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(N_{obs_i} - N_{pre_i}\right)^2}{n}} \tag{47}$$

$$\text{MAE} = \frac{\sum_{i=1}^{n}\left|X_{obs_i} - X_{pre_i}\right|}{n} \tag{48}$$

$$\text{rRMSE} = \sqrt{\frac{\sum_{i=1}^{n}\left(N_{obs_i} - N_{pre_i}\right)^2}{n}} \text{ x } 100 \tag{49}$$

$$PBIAS = \frac{\sum_{i=1}^{n}\left(X_{obs_i} - X_{pre_i}\right)}{\sum_{i=1}^{n}\left(X_{pre_i}\right)} \tag{50}$$

$$R = \frac{\sum_{i=1}^{n}\left(N_{obs_i} - \overline{N_{obs_i}}\right)\left(N_{pre_i} - \overline{N_{pre_i}}\right)}{\sqrt{\sum_{i=1}^{n}\left(N_{obs_i} - N_{obs_i}\right)^2 \sum_{i=1}^{n}\left(N_{pre_i} - N_{pre_i}\right)^2}} \tag{51}$$

Where, n is the number of observations, $_{obs}$ is the mean observed noise level, N_{obs} is the observed noise level, and N_{pre} is the predicted noise level.

Noise mapping

Noise maps show the acoustic environment in three dimensions, which may be employed in the analysis and management process. Noise maps are often created using commercial software that is GIS-based. The most common tasks performed with the GIS based program includes generation of grid points, computation of noise levels for grid points based on values measured at reference points using an interpolation approach, and the compilation of noise maps from grid points. The programs often use interpolation algorithms such as inverse distance weighted interpolation (IDW), Spline, Kriging, Natural Neighbor and Radial Basis Function (RBF). The technique for mapping is chosen based on the amount and dispersion of measurement points. The noise maps were created using ArcGIS 10.3 software for a better visual representation of the noise and its diurnal fluctuations in the research region. The IDW technique of interpolation is a point-based interpolation method. The value of vehicular traffic noise at the location *i* (N_0) is computed using the following expression.

$$\overline{N} = \frac{\sum_{i=1}^{nm} N_i P_i}{\sum_{i=1}^{nm} P_i} \tag{52}$$

Where n; stands for the number of reference points, Ni; symbolizes the vehicular traffic noise value at point i, Pi; represents the weight of the vehicular noise value at i point. Pi weights can be calculated as a function of the distance between the reference point and the interpolation point using Equation (53) below, based on the assumption that closer locations have a greater influence than distant ones.

$$P_i = \frac{1}{d_i^k} \quad i = 1,2,\ldots n \tag{53}$$

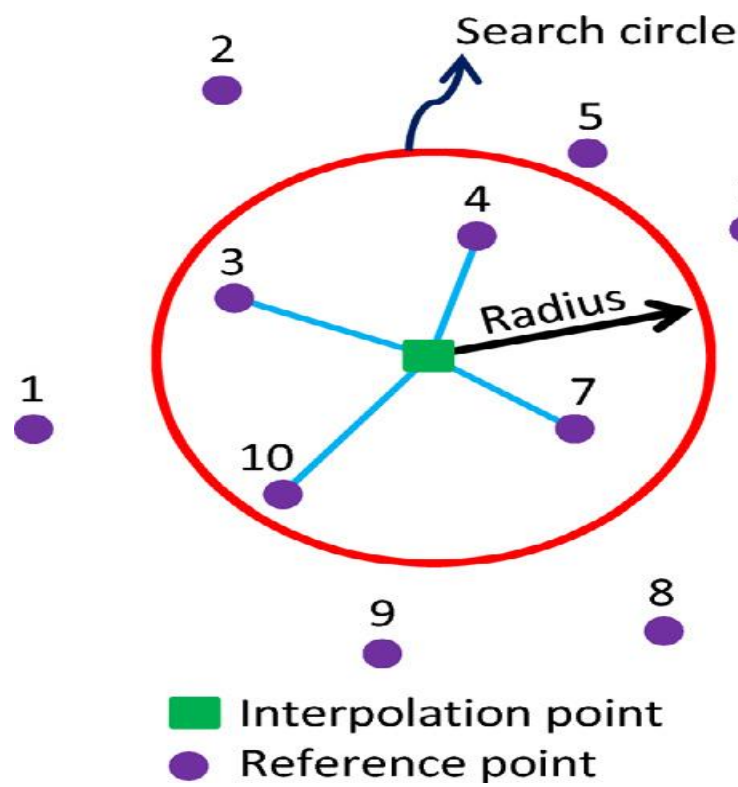
Where d_i is the horizontal distance between the interpolation point at (x_0, y_0) and the reference points at (x_i, y_i) and is calculated by the following formula (54). k is the power of the distance.

$$d_i = \sqrt{(x_i - x_0)^2 + (y_i - y_0)^2} \tag{54}$$

In the IDW approach, instead of using all of the reference positions in the research area, only the reference positions surrounding the interpolation positions can be used for the estimation of the vehicular traffic noise value. A defined search circle with a definite radius can be used to find the reference points for the interpolation computation. As a result, calculating the size of the search circle becomes a challenge. The spatial distribution of reference sites in the region, in addition to the distance amid them, are both important factors in determining the size of the search circle (Figure 16). At least three points equally spaced around the point must be utilized in order to compute the noise values acquired using the interpolation technique accurately. The search circle's utilization can have a considerable impact on the IDW method's performance (Ilker et al. 2016).

Figure 16

Search circle (Ilker et al. 2016)



The usage of exclusively ordinary neighbors of the interpolation point is another strategy distinct from this alternate option. If the Delaunay criteria are used to triangulate an interpolation point with its reference spots, the reference spots that form the triangle boundaries will be the interpolation point's ordinary neighbors (Macedonio and Pareschi 1991). As a result, these reference points are the only way to do interpolation with the

IDW. Natural neighbors eliminate the necessity to figure out the search circle's dimensions.

Chapter III Summary

The chapter provides the theoretical background of the different models used and the step-by-step methodology adopted for conducting the research. The chapter also described the different evaluation criteria used for assessing the performance of the models as well as the validation method used. The summary of the observed data as well as explanatory details of the measured data were discussed in this chapter.

CHAPTER IV

Results and Findings

Traffic noise in Nicosia, North Cyprus

The study dataset consists of 175 samples comprising C, HV (trucks, buses), MV (pickups and vans), V and the equivalent noise levels for 15 minutes intervals. The equivalent sound level, which was the target of the modelling, ranged between 56.3 and 80.5 dBA (see Table 2). The maximum noise level was observed during the evening along the Yakin Dogu Bulvari (point 10), which is the point with the highest average noise level (75.8 dBA) among all the observation points, while the lowest noise level was recorded in the morning observations at point 8. The average noise level in Nicosia, North Cyprus was 69.74 dBA which is less than the 70dB which according to World HealthOrganization (2000) and World Health Organization (2018), environmental and leisure-time noise with a LAeq,24h of 70 dB(A) or below will not cause hearing impairment in the large majority of people, even after a lifetime exposure. Figure 18 compares the average noise levels for morning and evening peak hours. It can be seen in Figure 17 that the average noise levels for evening peak hours is higher than the morning peak hours except for point 1, 2 and 11. The number of cars was measured between 36 to 981 with a mean value of 405 cars in 15-minutes. The maximum number of cars was recorded along Dr. Fazıl Küçük Bulvarı (point 5) during the evening hours, and the minimum number of cars was observed at Near East University (point 8) in the morning hours. The observed maximum number of heavy vehicles and medium vehicles during the data collection were 69 and 81, respectively, during the morning hours along Dr. Fazıl Küçük Bulvarı (point 5). The maximum number of buses was observed during evening hours along the Near East University Road (point 10). This is expected since the primary schools, junior college and college at the Near East University close at the same time (16:00 hrs.) and a disproportionate number of buses leave the university at virtually the same, which means they have to pass through the observation point along the Yakin Dogu Bulvari. The percentage of heavy vehicles in the traffic was moderate, with a maximum value of 29.8 % and an average of 4.9% of the traffic volume. The maximum and minimum average speed of 116km/hr and 35km/hr were observed at point 12 (expressway) and point 8 (local road), respectively, during the data collection. All the parameters recorded have reasonable ranges required for the modelling.

Table 2

Statistical summary of observed data

Parameter	Maximum	Minimum	Mean	Standard Deviation	Standard Error
Number of cars (C)	981	36	405.4	227.12	17.17
Number of van/pickups (V/P)	81	0	33.78	23.01	1.74
Number of buses (B)	42	0	8.87	7.65	0.58
Number of motorcycles (M)	24	0	5.27	4.68	0.35
Number of trucks (T)	46	0	10.67	10.66	0.81
Number of horns (H)	12	0	2.53	2.68	0.20
Average speed (kph) (V)	116	35	63.36	20.26	1.53
Noise level dB(A) (N)	80.5	56.3	69.74	5.03	0.38

All observations are for 15min duration

The summary of the maximum, minimum and average noise levels for the different road types and time of the day is presented in Table 3. The observation points were sited at places where traffic characteristics are the main factors contributing the traffic noise with little or no contribution from other sources such as commercial, industrial or heavy human activities. Therefore, noises from the vehicles' engines, rolling tires and aerodynamically generated noise by the moving vehicles are the major sources of the noise in all sites. The morning and evening peak hours traffic noise were compared in Figure 17.

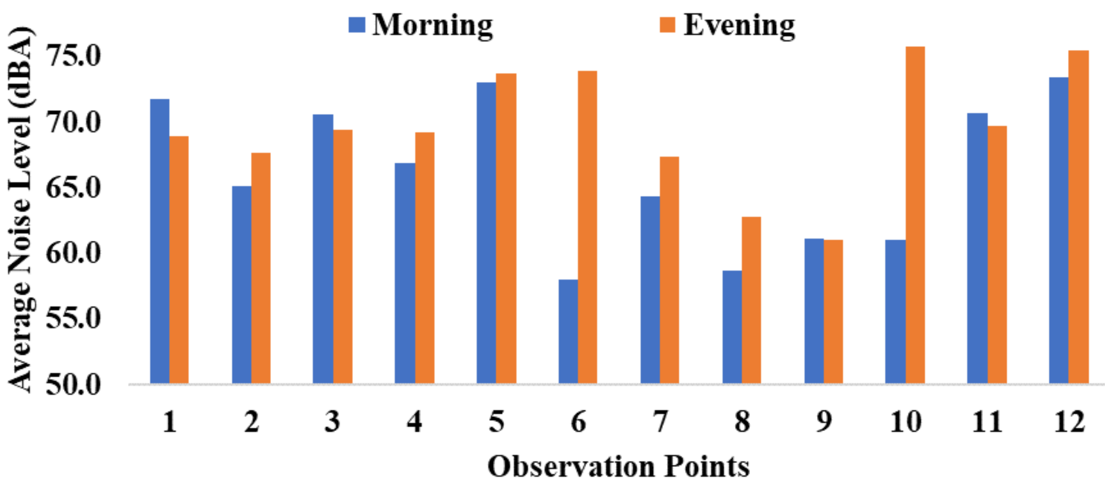
Table 3

Traffic noise level at the observation points

			Noise dB(A)		
Road Type	Observation Point	Time	Max	Min	Average
Arterial	1	Morning	75.9	70.7	71.8
		Afternoon	73.1	72.5	72.8
		Evening	69.1	68.4	68.9
	2	Morning	66.4	64.1	65.1
		Afternoon	69.4	62.8	66.8
		Evening	71.2	65.8	67.7
	3	Morning	71.5	69.1	70.6
		Afternoon	71.8	70.1	70.9
		Evening	70.4	68.8	69.4
	4	Morning	67.8	65.8	66.9
		Afternoon	66.8	65.8	66.2
		Evening	70.5	67.8	69.2
	5	Morning	73.6	72.2	73.0
		Afternoon	70.1	63.2	69.5
		Evening	74.2	73.4	73.7
Local	6	Morning	59.4	58.5	58.0
		Afternoon	64.9	58.1	61.1
		Evening	75.9	71.2	73.9
	7	Morning	65.8	63.5	64.4
		Afternoon	67.2	65.2	66.0
		Evening	69.5	64.2	67.4
	8	Morning	61.4	56.3	58.7
		Evening	67.2	60.1	62.8
	9	Morning	63.7	59.4	61.1
		Evening	62.5	58.4	61.0
Collector	10	Morning	78.2	59.0	61.0
		Evening	80.5	69.8	75.8
	11	Morning	73.0	69.9	70.7
		Evening	72.3	67.3	69.7
Expressway	12	Morning	74.3	72.6	73.4
		Evening	76.8	72.8	75.5

Figure 17

Comparison of measured noise levels for morning and evening peak hours



Noise mapping

Selection of base points for referencing is the most significant aspects of the IDW approach in order to estimate the interpolation point's noise value. For estimating the vehicular traffic noise values at the other locations through interpolation, a search circle with a definite radius must be defined. Therefore, only the points within the defined radius of the circle are used for the interpolation computation, rather than all of the reference points. The radius of should be determined such that at least three points evenly distributed around the centre may be considered for calculating grid points. As a result, any discontinuity on the map that will be constructed centred on the grid points will be avoided. The distance between neighbouring locations in the area determines the radius of the search circle. The distance between the neighbouring points must be compared with one another since that will make the selection of the search circle easier and helps in avoiding any discrepancies in the noise values of grid points to be utilized in map production. Conversely, if the distances between adjacent points are not comparable and are substantively unalike, computations for certain grid points can be done with appropriate allotment and appropriate number of points, while computations of other points may be done with least number of points with irregular distribution. In this situation, the resulting map will have some errors since the noise values for certain grid points deviate from what they ought to befall. Based on neighbouring point analysis, 750 m was found to be the least gridding range in this study. The influence of the noise level in the reference locations to the locations whose value is be determined is another significant component in the effectiveness of the IDW interpolation approach. The weight values are a result of the inversion of these distances, as the primary premise of this approach is for distant locations to have a larger weight in the computation than close points. A straight inversion of the distance can be utilized here, as well as the square, cube, or a bigger power of the inversion of the distance. The numbers 1, 2, 3, and 4 have been chosen for this study. To fully visualize the vehicular traffic noise level for the different observation periods (morning (8:00-10:00) and evening (16:00-18:00) peak hours) in all the sampling points, inverse distance weighted interpolation technique was used to map the noise information in the study area. The method was used considering its effectiveness in mapping traffic noise (Ahmad et al., 2010; Alam et al., 2018; Debnath & Singh, 2018). The average noise level for morning and evening observations were superimposed to ArcGIS map for development of the noise maps. A 5 dBA bandwidth was selected for producing the map and each bandwidth was represented by a different color recommended by Weninger, (2015) for noise mapping. This colour scale was selected over other colour scales (e.g Alberts and Alférez (2012)) because it provides color scale that is suitable even for people with colour deficiencies. The noise maps for the morning and the evening peak hours are shown in Figure 18 and Figure 19, respectively.

Figure 18

Noise map for the study area for Morning hours (8:00-10:00)

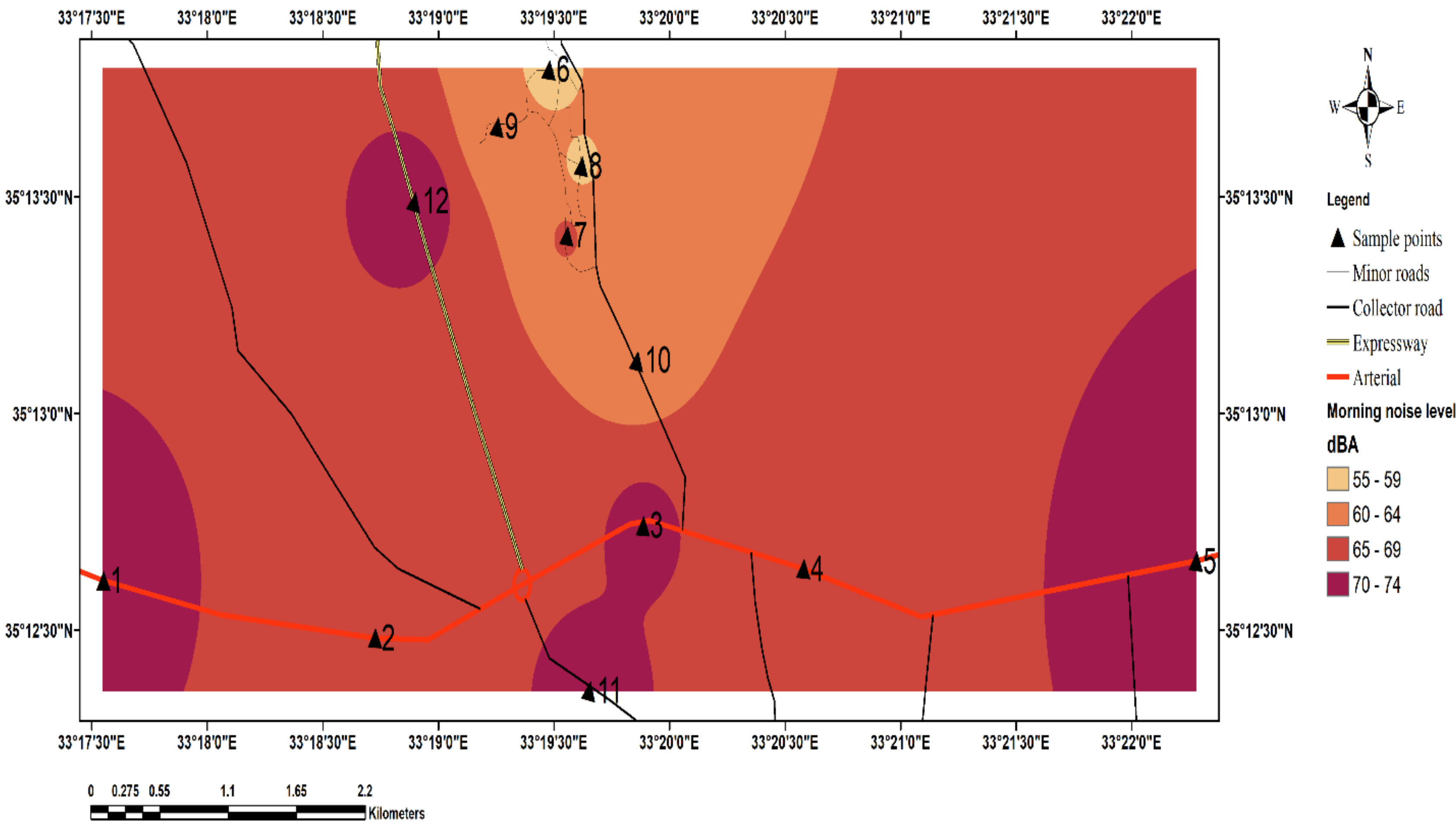
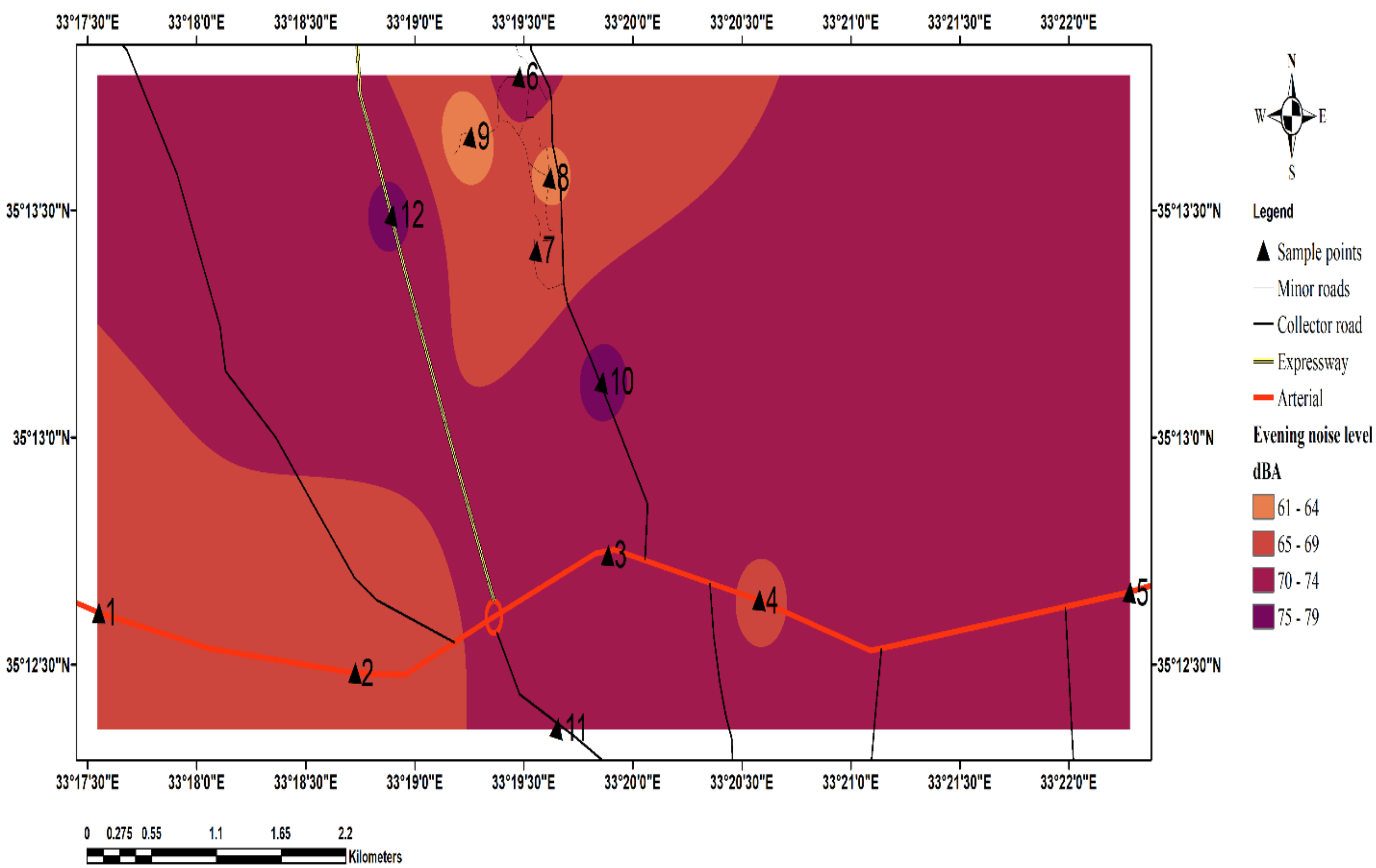


Figure 19

Noise map for the study area for evening hours (16:00-18:00)



The average noise level in the morning hours ranges from 58.0-73.4 dBA, with highest noise values at points 1, 5, 11 and 12. These points are on expressway, and major arterial which were characterized with high traffic volume. Lowest noise level was observed on the local roads (points 6, 7, 8 and 9) which were characterized with lower traffic volume and lower average speed. On the other side, the noise level in the evening ranges between 61.0-75.8dBA (Figure 19) which is 2.5 dB(A) higher than in the morning hours. The highest average noise level in the evening hours (>75 dBA) were observed at Points 10 and 12, while the minimum noise level was recorded on the local roads (8 and 9). For both morning and the evening observations, residents along the Expressway and major arterial are exposed to high noise level greater than 55dBA. A sustainable noise mitigation measures such as the use of sustainable metamaterial absorber (Danihelová et al. 2019), application of sonic crystals noise barriers made of recycled materials (Fredianelli et al., 2019b), use of electric car and car sharing which will help in reducing the overall traffic volume on the roads are therefore required along these class of roads to reduce the health hazards posed by incessant exposure to the noise level.

Result of Pearson correlation

The linear relationship between the input parameters and the traffic noise was determined using the Pearson correlation as shown in Figure 20. The result helped to preliminarily understand the nature of the interaction between the variable prior to the development of the nonlinear sensitivity analysis. It also helps reduce adding parameters that have strong linear relationship as input variables into single model thus reducing the issue of multi collinearity with significantly affects the performance of the model.

The result of the Pearson correlation matrix (Table 4) indicated strong linear relationship between the traffic noise and vehicles, cars, speed and medium trucks having values greater than 0.5. Number of motorcycles, and honking have least correlation with the traffic noise. This shows that the potential input parameters with high linear correlation with the traffic noise may be considered in the modelling even if they demonstrated a weaker nonlinear relationship in order to fully capture both linear and nonlinear pattern I the data.

Number of vehicles and cars a correlation coefficient of 0.9970 which is very close to one. For avoiding a multicollinearity problem, all models were developed with either number of cars as input parameter or number of vehicles to avoid obtaining erroneous result in a model were both were used as input parameters.

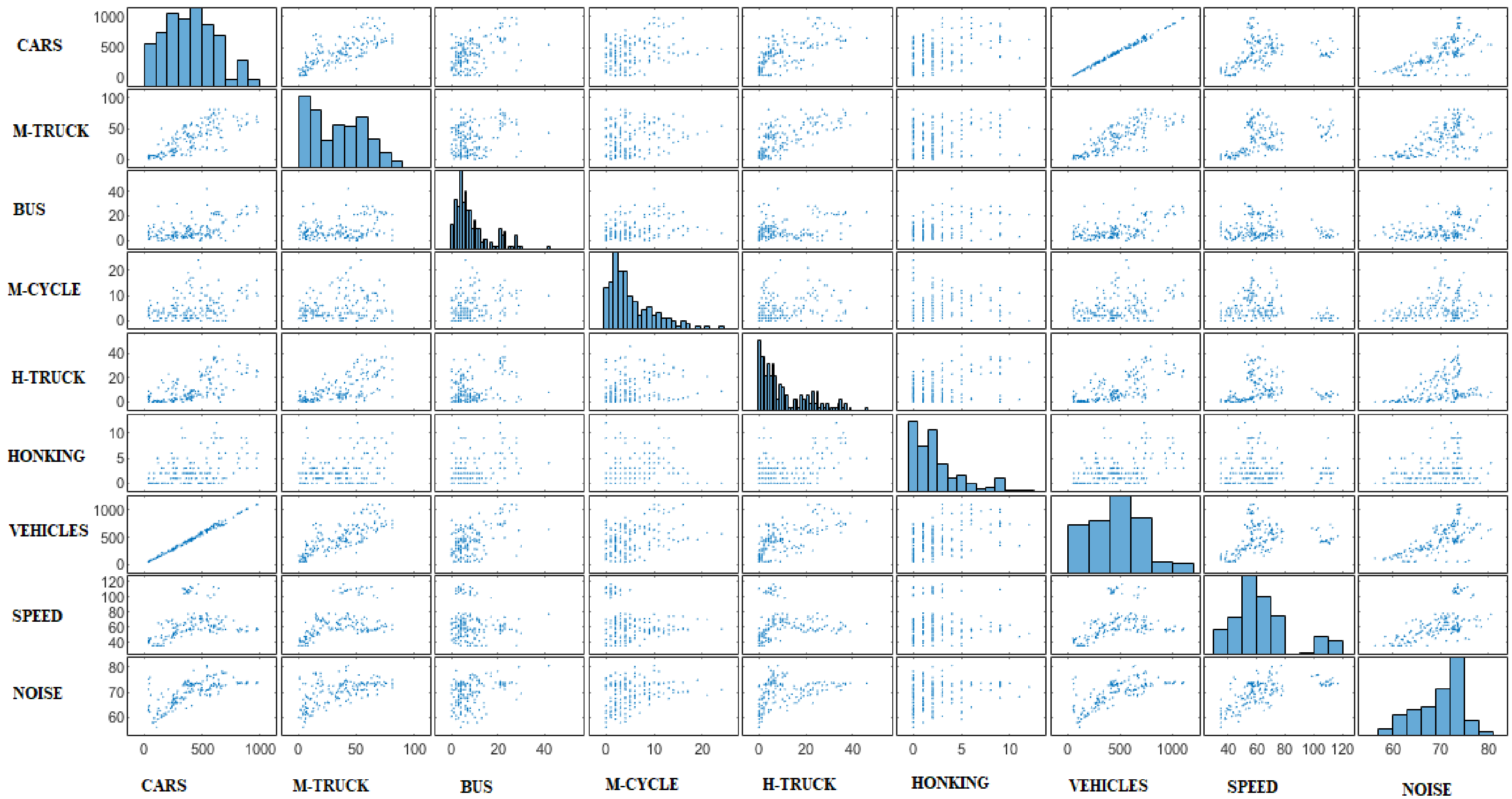
Table 4

Pearson correlation matrix

	cars	*Medium truck*	*Bus*	*M.cycle*	*Heavy truck*	*honking*	*vehicle*	*speed (kph)*	*dB(A)*
Cars	1								
Medium Truck	0.7581	1.0000							
Bus	0.5175	0.2994	1.0000						
M.Cycle	0.3559	0.1847	0.2921	1.0000					
Heavy Truck	0.6468	0.6959	0.3054	0.2239	1.0000				
Honking	0.4241	0.3141	0.4027	0.1145	0.4500	1.0000			
Vehicle	0.9970	0.7967	0.5308	0.3667	0.6859	0.4361	1.0000		
Speed (Kph)	0.3211	0.4624	-0.0865	-0.1670	0.0500	-0.009	0.3191	1.0000	
dB(A)	0.6999	0.5897	0.3707	0.2290	0.3917	0.2305	0.7001	0.5921	1.0000

Figure 20

Correlation matrix



Result of sensitivity analysis

Careful selection of dominant and most relevant factors in any black box modelling is an essential step in obtaining the optimum results. Due to the criticism of the correlation method that has previously been used to select dominant factors in noise level prediction (e.g. see Gan et al., 2012; Mansourkhaki et al., 2018). This study used three different types of sensitivity analysis (EANN based feature removal, single-input single-output neural sensitivity analysis and mutual information) were applied to determine the relationship and relative importance of the input parameters. The application of these methods in determining the nature of the relationship between the input and the target parameters was successfully employed in many studies (e.g. Giam and Olden, 2015; Hamad et al., 2017; Nourani et al., 2019c). In this study, MI, EANN-based feature removal and single-input single-output neural network-based sensitivity analysis were employed to determine the relative importance as well as the relationship the input parameters have with the traffic noise level (target). In the single-input single-output neural sensitivity analysis, each input parameter was imposed independently into an FFNN model to estimate the level of the roadway traffic noise. By doing that, the actual relationship between the parameter and the traffic noise level was determined without considering the influence of the other potential input variables. The models' performances (RMSE) were evaluated and the RMSE values of the models in the verification stage were used to rank the relative importance of the input parameters. The parameter with the lowest RMSE value was considered to be the most important input and the importance decreases as the error value increases. The results are presented in Table 5. A feature removal sensitivity analysis using the EANN model was also used to determine the relative importance of the input parameters. The procedure for the EANN-based feature removal sensitivity analysis involved four steps. In the first step, the EANN model was trained and tested using all the 6 potential input parameters (Q, C, MV, HV, V, P) as input variables to estimate the level of roadway traffic noise. Secondly, the performance (DC) of the model was computed. In the third step, one parameter (e.g. Q) was removed from the already trained and tested model, and the new model was trained and tested without that parameter (Q) and the corresponding DC value was computed. Lastly, the corresponding decrease in the DC value following the removal of the parameter Q at the testing stage was obtained and used to rank the relative importance of the parameter. The procedure was repeated for all the parameters and the results are given in Table 6. A higher reduction in the DC values indicates higher relative importance, while a lower reduction indicates less importance. As can be seen in the results of the EANN feature removal sensitivity analysis (Table 6), all the parameters are important in modeling the traffic noise as the removal of each of the parameters has caused a reduction in the DC value. Finally, for verification of the results of the AI-based sensitivity analysis methods, MI was used as an entropy-based criterion to determine the nonlinear statistical dependency of the road traffic noise level on the input variables. The results are presented in Table 7. As can be seen from the table, MI also ranked the parameters in a similar way to the AI-based methods. The ranking was exactly same as the EANN-based feature removal sensitivity analysis, indicating the higher accuracy of the EANN-based method.

Table 5

Single-input single output neural sensitivity analysis result

Input variable	RMSE*	Rank
Q	0.1431	1
C	0.1441	2
MV	0.1979	3
HV	0.2031	4
V	0.2163	5
P	0.2504	6

*RMSE has no unit, normalized data

Table 6

EANN-based feature sensitivity analysis result (DC0 = 0.9219)

Input variable removed	Decrease in DC (%)	Rank
Q	29	1
C	25	2
V	24	3
MV	17	4
HV	13	5
P	5	6

Table 7

Mutual information results

Variable	MI
Q	1.574001
C	1.573329
V	1.478594
MV	1.353831
HV	1.324476
P	1.200754

Single models result

Upon selection of the dominant parameters contributing to the road traffic noise (i.e. car, van/pickup, truck, average speed and bus), three nonlinear AI-based models (ANFIS, FFNN, SVR) and one linear black box model (MLR) were developed to estimate the level roadway noise in the city of Nicosia.

The FFNN model with five input variables (set 1) and one hidden layer was trained using the Levenberg-Marquardt algorithm to predict the noise level in the study area. For determining the optimal model structure, which is essential for obtaining the best result in the FFNN modelling, an iterative approach was employed by evaluating the performance of several models modelled with a different number of hidden neurons. The optimum structure was found with 8 number of neurons in the hidden layer. ANFIS model which is known to be a robust technique for modeling nonlinear relationships was also used in this study to model the traffic noise. The calibration of the membership functions (MFs) parameters in the ANFIS was done using the Sugeno fuzzy inference system through the hybrid algorithm. Trial and error method was used by changing the type of MF for obtaining the best result. The best ANFIS model was obtained using the Gaussian MF at 50 epochs. The third nonlinear AI model used in the study was the SVR model created using the radial basis function (RBF) kernel. The RBF kernel was utilized in the SVR model because it encompasses fewer tuning parameters than both the sigmoid and the polynomial algorithms. The RBF kernel often provides better results in SVR than other kernels (Sharghi et al., 2018). For more comparison and investigation, 2 additional input sets were considered and imposed into FFNN, ANFIS, SVR and MLR methods each containing the total traffic and speed as well as ratio of heavy vehicles in the traffic and honking for the second and third input datasets, respectively. The result of the three nonlinear AI-based models (ANFIS, FFNN, SVR) and one linear black box model (MLR) developed to estimate the level roadway traffic noise in the city of Nicosia for the three different inputs combinations is presented in Table 8.

Table 8

Performance results by single models for different input sets

Model input set	Input Combinations	Used method	Calibration		Verification	
			DC	RMSE*	DC	RMSE*
Set 1	Cars, van/pickup, truck, speed, buses	FFNN	0.7863	0.1338	0.7840	0.1492
		ANFIS	0.8981	0.0662	0.8670	0.1177
		SVR	0.8395	0.1154	0.7633	0.1570
		MLR	0.6680	0.1659	0.6607	0.1880
Set 2	Total traffic volume, speed, percentage of heavy vehicles	FFNN	0.7046	0.1564	0.6955	0.1781
		ANFIS	0.7544	0.1545	0.7121	0.1599
		SVR	0.8485	0.1256	0.7480	0.1445
		MLR	0.6470	0.1659	0.6341	0.1917
Set 3	Total traffic volume, speed, honking	FFNN	0.6727	0.1647	0.6618	0.1877
		ANFIS	0.6554	0.1894	0.5787	0.1869
		SVR	0.6485	0.1913	0.6256	0.1762
		MLR	0.5307	0.2095	0.4708	0.2211

*No unit for RMSE since data are normalized

Ensemble technique

In order to enhanced the efficiency of the single black box models, four different ensemble techniques combining the advantages of the single models were developed in the last step of the modelling. The outputs of the single models were fed as input parameters to the ensemble units. The SA and WA ensemble were modelled using equations 3.28 and 3.29, respectively. For the NE, the FFNN concept was used and selection of the optimum model was done by trial and error and the best structure was found to have 6 hidden neurons trained by 17 epochs. The AE was used in the research owing to the strength of the model demonstrated in the base models. The AE was modelled similar to that for single models using the outputs of the four black box models. The optimum model was found with the 'gbell' MF trained by 50 epochs. The results of the ensemble techniques are presented in Table 9.

Table 9

Results of the ensemble techniques

Ensemble	Calibration		Verification	
	DC	RMSE*	DC	RMSE*
SA	0.8754	0.1016	0.8059	0.1422
WA	0.8339	0.1173	0.8091	0.1410
NE	0.9424	0.0691	0.9038	0.1001
AE	0.9853	0.0349	0.9764	0.0496

*No unit for RMSE since data are normalized

Results of hybrid models

In the first stage, five data driven models including four AI-based models (BRT, FFNN, GPR, SVR) and a classical model (MLR) were developed for the prediction of roadway traffic noise, individually. The performances of these models were evaluated using four performance criteria (NSE, RMSE, MAE, CC) and the results are presented in Table 10. It should be noted that, several models were developed with each of the AI-technique using different structure, training algorithms and kernel functions but only the best models are reported in the Tables. For the FFNN model, the best result was obtained using 5-8-1 structure (8- neurons in the hidden layer) trained with the Levenberg Marquardt algorithm and tan-sigmoid activation function. The best models for the SVR, BRT and GPR were obtained using RBF kernel, least square boost algorithm and squared exponential kernel which is the most commonly used kernel for GPR models (Athavale et al. 2019), respectively.

Table 10

Performance of single models for prediction of roadway traffic noise level

Model	Calibration				Verification			
	NSE	RMSE*	MAE*	rRMSE*	NSE	RMSE*	MAE*	rRMSE*
FFNN	0.7857	0.0754	0.0534	13.6005	0.7850	0.1325	0.1035	23.9084
SVR	0.8406	0.0650	0.0417	11.7299	0.7619	0.1394	0.0952	25.1564
BRT	0.9110	0.0592	0.0464	10.6796	0.8679	0.0852	0.0626	15.3848
GPR	0.8687	0.0590	0.0389	10.6452	0.8282	0.1184	0.0882	21.3712
MLR	0.6707	0.0934	0.0724	16.8603	0.6586	0.1669	0.1214	30.1236

*No unit for normalized data

For enhancing the prediction ability of the single models in this study, four different linear-nonlinear hybrid models were developed in the second part of the study where the results of the hybrid models are shown in Table 11.

Table 11

Performance of hybrid models for prediction of traffic noise level

Models	Calibration				Verification			
	NSE	RMSE*	MAE*	rRMSE*	NSE	RMSE*	MAE*	rRMSE*
MLR-FFNN	0.9657	0.0529	0.0450	9.9861	0.8845	0.0553	0.0422	9.5447
MLR-SVR	0.9610	0.0564	0.0465	10.1826	0.8723	0.0582	0.0470	10.5005
MLR-BRT	0.9440	0.0676	0.0398	8.8154	0.9100	0.0488	0.0529	12.1971
MLR-GPR	0.9793	0.0411	0.0350	7.7069	0.9312	0.0427	0.0347	7.4249

*No unit for normalized data

Results of EANN model

Two scenarios were considered for modeling the road traffic noise based on different input combinations for the EANN models. In the first scenario, the vehicular classification (C, MV, HV) and V were used as the model's inputs. In the second scenario, Q, P and V were considered as the input parameters to the model. Different classes of vehicles have different acoustic signatures and will therefore make different contributions to the road traffic noise level. This why Scenario 1 has vehicles classifications as the input variables. By feeding the vehicle classes into the AI models, the complexity of the AI model will be reduced and hence, it can enhance the performance of the model and decrease the time required for the numerical computation. The input combination in Scenario 2 was used because most of the established empirical models have Q and P as input parameters instead of the classification (e.g. CoRTN model, BURGESS, RLS90, C.S.T.B (Garg and Maji 2014)) to determine if classifying the traffic into subcategories has any effect on the overall models' performances or not.

Therefore, in Scenario 1, the mathematical relationship can be expressed as:

$$L_{eq} = f\,(C, MV, HV, V) \tag{55}$$

While for Scenario 2, the relationship can be expressed as:

$$L_{eq} = f\,(Q, P, V) \tag{56}$$

In this stage, FFNN as a conventional neural network and EANN as a new generation of neural networks were applied for the estimation of the road traffic noise level in Nicosia. MATLAB 2018a toolbox was used for the development of the FFNN model, while a MATLAB code was developed to train the EANN model. The three-layer FFNN with one input layer, one hidden layer, and one output layer was trained using the Levenberg Marquardt scheme of backpropagation algorithm. Similarly, a simplified form of EANN training using the backpropagation algorithm was applied for modeling the road traffic noise for both scenarios. A good model structure is necessary for obtaining a good result in the neural network models. Consequently, a hypersensitivity analysis by changing the number of hidden neurons (2-30), emotional hormones (1-20), training epochs (10-100), percentage of data for training (60-80), and activation function (tansig, logsig, purelin) was performed for determining the best model structure. The optimum structures of the model for the two scenarios were obtained using the trial-and-error method. The model structure that gave the highest DC and lowest RMSE values in the verification stage was chosen as the best model. For comparison, the conventional multilinear regression model (MLR) was also used to estimate the level of road traffic noise for both scenarios.

The results of the black box models (EANN, FFNN and MLR) for the two scenarios are presented in Table 12. It should be noted that only the results of the best models were reported. The EANN demonstrated higher performance efficiency for both scenarios. The results showed that application of the EANN model enhanced the efficiency of the ordinary FFNN in Scenario 1 by 9 % and up to 14% in Scenario 2. The improvement in the performance was due to the incorporation of the artificial hormones into the feedback intwine between hormones and neurons in the EANN model.

Table 12

Results of EANN, FFNN and MLR models for both scenarios 1 and 2

Models	Scenario	Number of Hormones	Number of hidden neurons	DC		RMSE*	
				Calibration	Verification	Calibration	Verification
EANN	1	5	10	0.8858	0.8094	0.0443	0.1026
	2	3	10	0.7627	0.7321	0.0473	0.1059
FFNN	1	-	10	0.7688	0.7167	0.0539	0.2106
	2	-	7	0.6590	0.5910	0.0717	0.2310
MLR	1	-	-	0.5839	0.4510	0.1206	0.1831
	2	-	-	0.5451	0.3723	0.1289	0.1914

*RMSE has no unit, normalized data

Comparing the performance of the three developed data driven models (ensemble, hybrid and EANN)

The best results for the ensemble model (AE), hybrid model (MLR-GPR) and the EANN model (scenario I) were compared (Table 13 and Figure 21) and the result indicated higher prediction accuracy of the ensemble modelling than the remaining two proposed models having highest NSE value of 0.9764 and normalized RMSE value of 0.0496 in the verification stage. Both hybrid and ensemble models demonstrated higher accuracy than the EANN. This is because both hybrid and the ensemble models captured both linear and nonlinear pattern in the data by combining linear and nonlinear models in the modelling stage which the EANN lacks. The study shows that the ensemble modelling could improve the prediction accuracy of the hybrid and EANN model by 4.5% and 16.7%, respectively in the verification stage. The findings of the study was supported by a comparative study of ensemble modelling, hybrid EANN-GA and EANN model by (Abba et al. 2021). The higher performance of the ensemble approach is due to its ability to combine the unique advantage of each of the base models.

Table 13

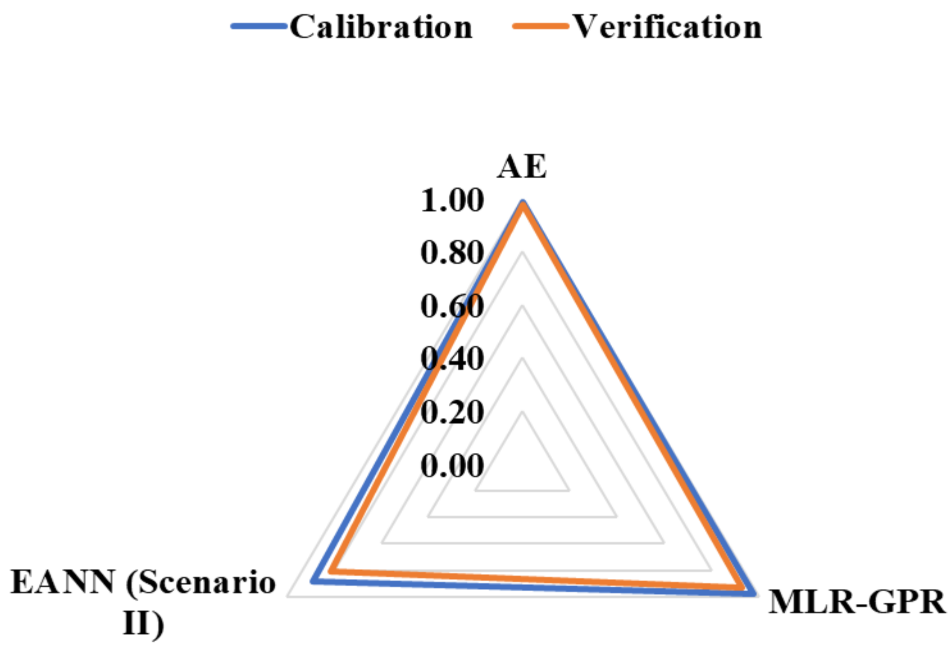
Comparing the results of the ensemble techniques, hybrid and EANN

Models	Calibration		Verification	
	DC	RMSE*	DC	RMSE*
AE	0.9853	0.0349	0.9764	0.0496
MLR-GPR	0.9793	0.0411	0.9312	0.0427
EANN (Scenario II)	0.8858	0.0443	0.8094	0.1026

*No unit for RMSE since data are normalized

Figure 21

Radar plot comparing the three different models



Traffic noise-air pollution interactions

The percentage of the world's population residing in urban centers is about 54% resulting in an increasing volume of vehicular traffic in the major streets of urban areas. The assessment of combined exposure effect to air and noise pollution is necessary and could be one of the major challenges of the present due the unavailability of the tools to facilitate the assessments (Tenailleau et al. 2016). For determining the interaction between air pollutants and traffic noise in this study, $PM_{2.5}$ was selected as the air pollutant to be used. This is because $PM_{2.5}$ acts as the major indicator for air quality monitor system (Donkelaar et al. 2006) and 64% of the $PM_{2.5}$ was reported to come from the vehicular traffic (European Environment Agency 2012). Also, both traffic noise and $PM_{2.5}$ are mostly generated by traffic flow and increased with increasing traffic volume (Nourani et al. 2020a).

A correlation matrix in Table 14 was used as a preliminarily measure for obtaining the linear relationships between $PM_{2.5}$ and other potential input parameters. The result shows that most of the input parameters have a reasonable correlation (>0.5) with $PM_{2.5}$ with the exception of CO_2 and SO_2 having a correlation coefficient of 0.02. The highest correlation coefficient was found between traffic and the number of cars. This is because cars constitute more than 90% of the traffic volume in the area with virtually same standard deviation (29). The correlation between $Pm_{2.5}$ and traffic noise is 0.57 which is supported by studies conducted by Gan et al., (2012).

In the first stage of the study, a group sensitivity analysis using the SVR model was conducted for two scenarios. The SVR model was used for the group sensitivity analysis in this stage due to its high performance as mentioned by (Nourani and Sharghi 2020). In scenario I, traffic noise was not added as input parameter for the models while in scenario II, all the model includes traffic noise as an input parameter. Four models were developed in each scenario as giving in Equations 4.6-4.13.

Scenario I;

M1; $PM_{2.5} = f\,(CO_2, CO, SO_2, PM_{10})$ (57)

M2; $PM_{2.5} = f\,(WS, Wdir, Temp, RH)$ (58)

M3; $PM_{2.5} = f\,(truck, medium\ veh, Bus, cars)$ (59)

M4; $PM_{2.5}$ = f (CO_2, CO, SO_2, PM_{10}, WS, Wdir, Temp, RH, truck, medium veh, Bus, cars) (60)

Scenario II;

N1; $PM_{2.5} = f\,(CO_2, CO, SO_2, PM_{10}, traffic\ noise)$ (61)

N2; $PM_{2.5} = f\,(WS, Wdir, Temp, RH, traffic\ noise)$ (62)

N3; $PM_{2.5} = f\,(truck, medium\ veh, Bus, cars, traffic\ noise)$ (63)

N4; $PM_{2.5} = f\,(CO_2, CO, SO_2, PM_{10}, WS, Wdir, Temp, RH, truck, medium\ veh, Bus, cars, traffic\ noise)$ (64)

Table 14

Correlation matrix

Parameters	*RH (%)*	*Temp (oC)*	*Wdir (deg)*	*WS (kph)*	*Traffic*	*cars*	*Bus*	*medium veh*	*truck*	*P*	*CO2 (ppm)*	*CO (ppm)*	*NO2 (ppb)*	*SO2 (ppb)*	*PM10 (ug/m3)*	*Noise*	*PM2.5(ug/m3*
RH (%)	1																
Temp (oC)	0.65	1															
Wdir (deg)	-0.59	-0.54	1														
WS (kph)	0.47	0.06	-0.1	1													
Traffic	-0.61	-0.37	0.46	-0.31	1												
cars	-0.65	-0.45	0.49	-0.29	0.98	1											
Bus	-0.29	0.08	0.26	-0.3	0.48	0.38	1										
medium veh	0.19	0.34	-0.27	0.03	-0.06	-0.19	0.02	1									
truck	0.57	0.52	-0.28	0.18	-0.19	-0.29	0.01	0.32	1								
P	0.39	0.53	-0.17	0.01	-0.15	-0.29	0.61	0.23	0.68	1							
CO2 (ppm)	-0.47	-0.67	0.42	-0.02	0.09	0.16	-0.26	-0.16	-0.36	-0.43	1						
CO (ppm)	-0.35	-0.05	0.51	-0.28	0.46	0.43	0.41	-0.14	0.04	0.12	-0.03	1					
NO2 (ppb)	0.78	0.62	-0.48	0.11	-0.55	-0.6	-0.15	0.18	0.55	0.46	-0.24	-0.26	1				
SO2 (ppb)	0	-0.19	-0.14	-0.01	-0.14	-0.11	-0.32	0.16	-0.15	-0.24	0.57	-0.42	0.08	1			
PM10 (ug/m3)	0.57	0.56	-0.49	-0.22	-0.51	-0.56	-0.21	0.33	0.39	0.28	-0.27	-0.32	0.77	0.09	1		
Noise	-0.63	-0.66	0.41	-0.11	0.38	0.43	0.06	-0.22	-0.41	-0.36	0.51	0.11	-0.57	0.04	-0.6	1	
PM2.5(ug/	0.71	0.69	-0.45	0.13	-0.38	-0.45	-0.16	0.35	0.59	0.4	-0.36	-0.2	0.76	-0.02	0.69	0.57	1

The results of the group sensitivity analysis for scenario 1 and scenario II are presented in Table 15 and Table 16, respectively. The result of the group sensitivity analysis has demonstrated higher relevance of the air pollutants followed by the meteorological parameters and lastly the traffic data. The result also indicated that inclusion of traffic noise into $PM_{2.5}$ (N1-4) could improve the performance could increase the performance of M1, M2, M3 and M4 for the prediction of $PM_{2.5}$ by up to 11.23%, 2.17%, 36.54%, 5.24%, respectively in the verification stage.

Table 15

Results of the $PM_{2.5}$ concentration model using different inputs groups without traffic noise (scenario I)

MODELS	Inputs	NSE	RMSE	R	PBIAS	NSE	RMSE	R	PBIAS
		Training				Verification			
M1	P	0.7620	0.1190	0.8776	0.2310	0.6276	0.0917	0.5577	0.4218
M2	M	0.6674	0.1407	0.8227	0.2801	0.6713	0.0862	0.6874	0.4253
M3	T	0.5517	0.1006	0.5180	0.4676	0.2116	0.2166	0.5265	0.4805
M4	P,M,T	0.8155	0.1048	0.9082	0.1508	0.8118	0.0652	0.7997	0.3069

Table 16

Results of $PM_{2.5}$ concentration model using different inputs groups with traffic noise (scenario II)

Models	Inputs	NSE	RMSE	R	PBIAS	NSE	RMSE	R	PBIAS
		Training				Verification			
N1	P	0.7969	0.1178	0.8742	0.2271	0.7399	0.0810	0.6779	0.3680
N2	M	0.7438	0.1305	0.8592	0.2620	0.6930	0.0873	0.6168	0.4217
N3	T	0.6390	0.1525	0.7739	0.2757	0.5770	0.1012	0.3577	0.4671
N4	P,M,T	0.8827	0.0577	0.9207	0.2572	0.8642	0.0993	0.8536	0.1509

Chapter IV Summary

The chapter presented the results and findings of the research. The average traffic noise in the study area was found to be 69.74dBA and the noise was found to be higher during the evening hours than morning hours. The result of the second phase of the study has shown that the inclusion of traffic noise in modelling the $PM_{2.5}$ could improve the performance of the model by up to 12% in the verification stage. The $Pm_{2.5}$ concentration in the study area was also found to be 5.28 ug/m^3 higher than the optimal level of 25 ug/m^3 recommended by WHO.

CHAPTER V

Discussions

Traffic noise in Nicosia, North Cyprus

A total of 175 data samples were gathered for conducting the research. The summary of the data collected for the study is presented in Table 2. The noise level in the study area was measured between 56.3 and 80.5 dB(A) with an average value of 69.7 dB(A) which is slightly lower than the 70dB that is believed not to cause any hearing impairment even after a lifetime exposure (World HealthOrganization, 2000). The highest noise was observed during the evening hours along a secondary road (Point 10) and the lowest noise level was recorded on a local road at observation point 8. The average traffic volume for the 15-minutes observation in the study area was 464 vehicles. The maximum traffic volume of 1,108 vehicles was observed in the evening hours at observation point 5 which is on a major arterial and the minimum value of 49 vehicles was also observed in the evening hours at point 6 (local road). The percentage of the truck in traffic stream is low with maximum of 16.4% and the average is 2.3% of the total traffic volume. The average speed of the vehicles ranges between 35-116kph. The maximum speed was observed in the morning hours on the motorway (point 12) which was expected since the free flow speed on motorway is usually high compared to other classes of highways. The lowest speed was also observed in the morning on a local road (point 8). The number of horns in each observation period was relatively low with an average of 3 honks in 15 minutes.

The highest noise level of 80.5 dB(A) was observed at observation point 10 at the evening hours. This observation point is located along Near East University Road which is the only road linking Near East University with the major road. It has highest percentage of buses traversing the point and relatively high speed second to that of expressway which is believed to have high contribution to traffic noise, also 80% of the vehicles observed here were cars which are the main factor contributing to the traffic noise. Another explanation for recording this high noise at point 10 is that, aerodynamically generated noise is high since there were no high buildings around the area to serve as barriers within vicinity of the observation point. Minimum noise level of 56.3 dB(A) was observed at point 8. This point is on a local road where traffic and average speed are low. Since the traffic noise has direct relationship with traffic volume, and it increases with increasing traffic (Mehdi et al. 2018), point 8 was expected to record the least noise level in the morning hours having only total traffic volume of 115 vehicles in 15 minutes. The roadway traffic noise level in the study area is greater in the evening, followed by morning hours. The lowest noise level was observed during the afternoon observation. This is understandable since the peak traffic flow was observed in the evening and morning hours with highest peak hour in the evening. The result corroborates with research by Debnath & Singh (2018). On the basis of road type, the highest average noise level was observed on the expressway, collector road, arterial road, and local road respectively in order of the speed observed on the roads. This shows that speed is a significant factor for noise generation.

Sensitivity analysis

The selection of the main input parameters in AI modeling is a critical issue for achieving appropriate results. In that regard, a nonlinear sensitivity analysis was conducted in the study to determine the importance and rank of the traffic noise predictors (C, MV, HV, Q, P and V) in modeling the road traffic noise level. It was also used to determine the nature of the relationship between the input parameters and the noise in the study area. Previous studies have employed the use of the conventional linear correlation coefficients for the selection of dominant input parameters and the determination of relative importance of the individual parameters in AI models (e.g. Elkiran et al., 2018). However, the method has already been criticized for selecting input parameters in modelling nonlinear problems, since a nonlinear relationship may exist between the input and the target parameters (Nourani et al., 2014). Due to the criticism of the correlation method for selecting the dominant parameters, researchers have shifted to nonlinear sensitivity analysis methods such as the single-input single-output neural sensitivity analysis (Nourani et al., 2019b; Nourani et al., 2019c), feature removal/R^2 metric sensitivity analysis (Giam and Olden 2015; Hamad et al. 2017), partial derivative sensitivity analysis (Shaghaghi et al. 2017), and mutual information (MI) (Nourani et al.

2015), etc. In this study, three different types of sensitivity analysis (EANN based feature removal, single-input single-output neural sensitivity analysis and mutual information) were applied to determine the relationship and relative importance of the input parameters. The application of these methods in determining the nature of the relationship between the input and the target parameters was successfully employed in many studies (e.g. Giam and Olden, 2015; Hamad et al., 2017; Nourani et al., 2019c).

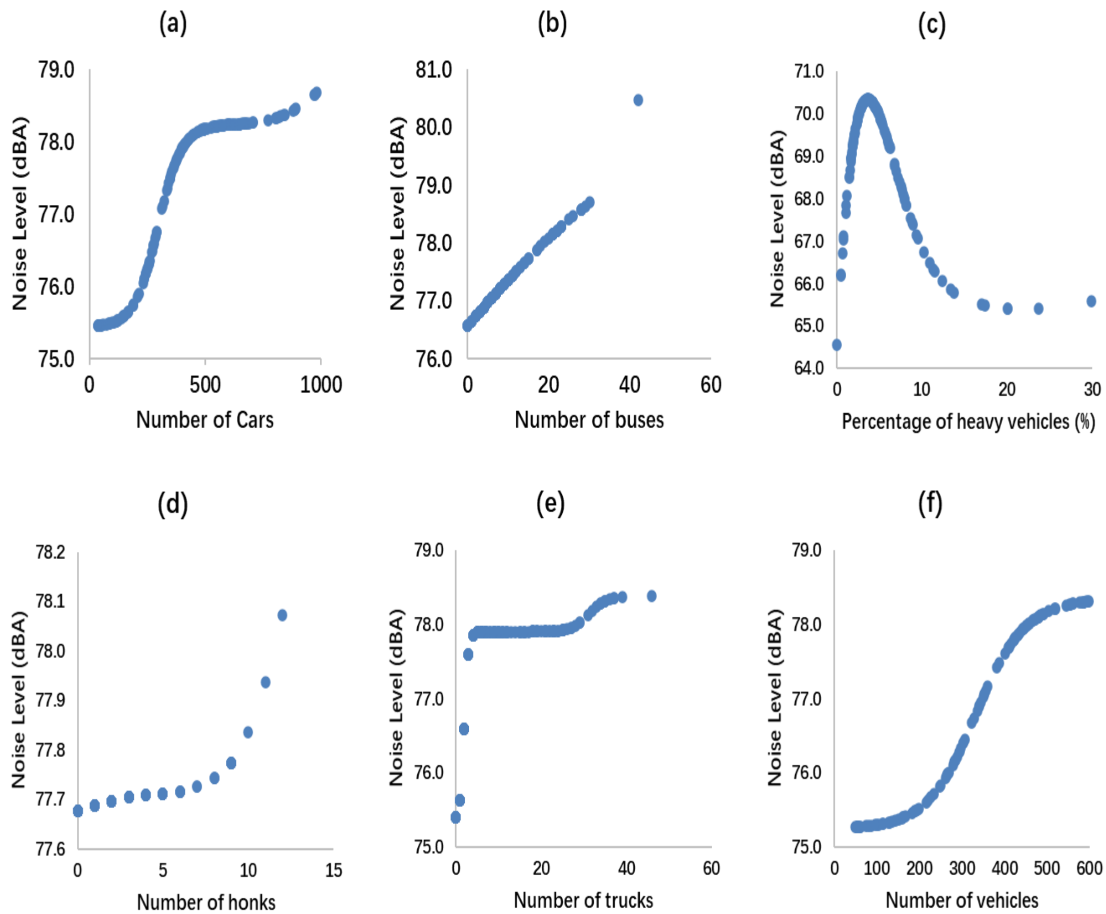
From the results of the two AI-based sensitivity analyses (Tables 5 and 6), it can be seen that Q and C were the most relevant input parameters and P was found to be the least pertinent input as they were 1st, 2nd and 6th, respectively. The outcome of the result is supported by a study conducted in Patiala, India by Singh et al., (2016). Similarly, the percentage of heavy vehicles was found to be the least relevant among the factors (distance of the receiver from edge of the road, temperature, volume of light and heavy vehicles, speed and percentage of heavy vehicles) examined in the work of Ali et al., (2019), who used a hybrid ANN and forward sequential feature selection. C, MV and HV were ranked 2nd, 3rd, and 4th, respectively, in the single-input single-output sensitivity analysis, while in the feature removal sensitivity analysis, the parameters were ranked 2nd, 4th, and 5th, respectively. It is important to note that, in both methods, C is the most important vehicle class followed by MV and lastly, HV. This is due to the traffic composition in the study area, where C dominated the traffic. V was ranked 5th in the single-input single-output sensitivity analysis, while in the feature removal sensitivity analysis, it was ranked 3rd, resulting in a decrease in the DC level of up to 24%. This is because the EANN model, which has a higher capability to map input and output with precision was used for ranking the importance of the parameters in the feature removal sensitivity analysis. Therefore, the error in estimating the noise level in the single-input single-output model using the speed of the vehicles along the different road classes is minimized, resulting in higher accuracy in the EANN-based sensitivity analysis. Both sensitivity analysis methods were found to be good in ranking the input parameters. Finally, for verification of the results of the AI-based sensitivity analysis methods, MI was used as an entropy-based criterion to determine the nonlinear statistical dependency of the road traffic noise level on the input variables. As can be seen from the tables, MI also ranked the parameters in a similar way to the AI-based methods. The ranking was exactly same as the EANN-based feature removal sensitivity analysis, indicating the higher accuracy of the EANN-based method.

In order to determine the nature of the interaction amid the input parameters and the target (noise level), the estimated noise level obtained from the single-input single-output model was plotted for all parameters, as shown in Figure 22. It can be seen that all the parameters have a nonlinear direct relationship with the traffic noise level. The traffic noise increased significantly with an increase in C for values between 200-500, but as the volume of C exceeded 500, the increase in the traffic noise became lower as the values of C increased (Figure 22a). For HV, the traffic noise increased at a faster rate with an increase in HV (0 up to 25), but above 25, the increase in traffic noise became slower (Figure 22b). An increase in P (for values up to 5%) was directly proportional to the noise level, but for values above 5%, P showed an inverse nonlinear interaction with the level of the roadway traffic noise. The decrease in the noise level was higher for values between 5% and 15% but was low for the values above 15% (Figure 22c). The results obtained for P are supported by a study conducted in Sharjah, UAE (Hamad et al., 2017). The number of MV had little or no effect on the traffic noise up to 10 van/pickups, but a slight increase in the noise level occurred as the number exceeded 10 (Figure 22d). The increase in the traffic noise due to an increase in V was also higher at a lower speed (20-50 kmph) than at higher speed (Figure 22e), which was similar to the result obtained in Sharjah, Dubai by Hamad et al., (2017). An increase in the V values from 20 to about 40 kmph increased the noise level by about 3dBA and the was supported by another study where an increase of 4-5 dBA was observed as a result of an increase in V from 25-35kmph (see, Vijay et al., 2015). The relationship between Q and the traffic noise was similar to that of C, where the noise level tended to increase at a higher rate when the traffic was low (<600 vehicles, see Figure 22f). An increase in the traffic noise level as a result of an increase in Q has also been reported by various other studies (e.g. see, Zannin and Ferraz 2016; Mehdi et al., 2018).

The relationships obtained from the sensitivity analysis of the input parameters could be discussed physically since traffic volume (comprising of C, MV, HV) and speed were reported to contribute immensely to traffic noise level (Vijay et al. 2015; Mehdi et al. 2018). This is due to the inverse relationship that exists between speed, density and flow (Gaddam and Rao 2019). A high value of V indicates a higher degree of freedom by the drivers, which in turn indicates low density and therefore lower traffic volume on the roads. Since Q and V are believed to be the major contributors to noise, a small increase in any of the vehicle class will significantly increase the components of the traffic noise (tire-pavement noise, aerodynamically generated noise due to vehicle movement, engine noise) if other parameters are not considered. For this reason, at low Q values, where the level of service is high, the increase in the noise level was high due to contributions from both Q and V, as seen in Figure 21, but as the traffic flow increased, the level of service decreased, as well as the average speed. Therefore, the overall increase in the traffic noise would be small even though the Q continues to increase because the contribution from V has decreased and vice versa. At capacity (near congestion), only noise from the vehicle engines contributed to the traffic noise level, but noise due to tire-pavement interactions and aerodynamically generated noise as a result of vehicle movement will be less, this causing a lower noise level. This is why at higher values of Q (>600), the increase in traffic noise was small. The decrease in the noise level when P was high was expected because higher P values were reported to have an inverse relationship with road density (Chandra et al. 2016) and road density has a direct relationship with the traffic noise level at any given time. This is because HV occupy larger spaces on the road and mostly move at lower speeds compared to other classes of vehicles on the road, thus reducing the overall Q and V values. The three different shapes for V (Figure 22e) at lower speed values may be due to the different road classes (expressway, arterial, collector and local road) considered in the study area, each of which have different speed limits.

Figure 22

Sensitivity analysis of the input parameters (a) Number of cars (b) Number of heavy vehicles (c) percentage of heavy vehicles (d) Number of medium vehicles (e) Average speed (f) number of vehicles



Single models result

To further examine the performance level of each of the developed models (AI), MLR model which is based on a linear correlation between the noise level and the noise predictors was also employed. The MLR model which is based on a linear relationship between the noise and its predictors is inferior to the AI models. This is because the traffic noise level is a nonlinear process and may accurately be modeled using a nonlinear technique instead of the linear model. The ANFIS model outperformed all the single models in the prediction of traffic noise, followed by the FFNN, SVR and lastly the MLR models. This is because the ANFIS model combined the advantages of the FFNN model and the fuzzy inference system for handling uncertainties. The result is supported by other studies that compared the performances of the ANN and ANFIS for noise prediction (Codur et al., 2017). The application of the AI models could improve the performance of the MLR model in the verification step by 20%, 12% and 10% using ANFIS, FFNN and SVR models, respectively. The scatter plots for the results of single models (set 1) in the calibration and verification stages are presented in Figure 23.

In some previous studies which used AI models for traffic noise prediction, total traffic volume has been considered as an input of the models instead of imposing classified number of vehicles such as number of cars, vans, trucks, buses and motorcycles (e.g. see Codur et al., 2017; Mansourkhaki et al., 2018). Accordingly, for more comparison and investigation, 2 additional input sets were considered and imposed into FFNN, ANFIS, SVR and MLR methods each containing the total traffic and speed as well as ratio of heavy vehicles in the traffic and honking for the second and third input datasets, respectively. The results of the modelling using these input datasets (as set 2 and set 3) presented in Table 8 indicate that using the total traffic volume as input variable instead of classifying the vehicles into different categories (cars, van/pickup, truck, bus, motorcycles) may reduce the performance of the applied models. The performance of the modelling using input dataset 2 was dropped by 15%, 9%, and 1% for ANFIS, ANN, and SVR models, receptively. For the modelling using input dataset 3, the performance was decreased by 29%, 12% and 13% for ANFIS, ANN and SVR, respectively. It seems inclusion of irrelevant parameter of honking in input set 3 led to more reduction in the modelling performance.

The performance of the AI based methods in the prediction of noise level was further investigated by comparing the results obtained by the black box methods with results of some established classical models. The classical methods used for the comparison were the CNR model, RLS90 model (Garg and Maji, 2014) and the Burgess' model (Quartieri et al. 2009). The expressions for determining the noise levels using the aforementioned classical models are given by:

CNR: N = 35.1 + 10log (+) – 10log+ 1.5 (65)

RLS90: N = 37.5+log (66)

BURGESS: N = 55.5 + 10.2logQ + 0.3P – 19.3log(d) (67)

Where, P and d present total traffic flow, number of light vehicles, number of heavy vehicles, percentage of heavy vehicles and distance from the noise source which was considered to be 4m in this study (average distance), respectively. The obtained results of the applied classical models are presented in Table 17.

Table 17

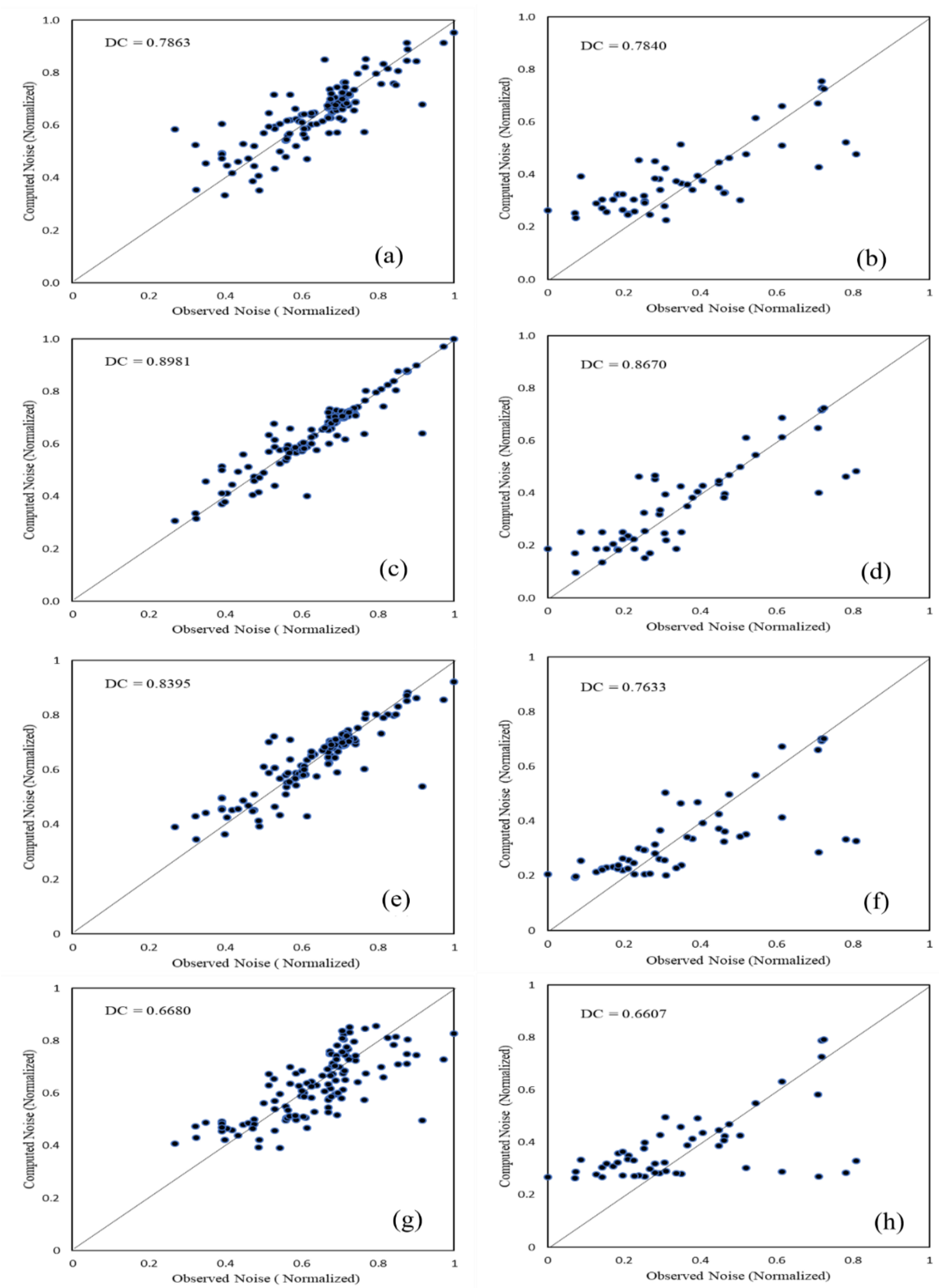
Results of the classical models

Models	DC	RMSE dB(A)
CNR	0.4342	3.7693
BURGESS	0.3580	4.0150
RLS90	0.1268	4.6826

Comparing the result of the AI based models (Table 8) and that of the classical models (Table 17) revealed that, the AI based models have better estimation capability than the classical models in estimating traffic noise due to their ability in modelling complex and nonlinear process like traffic noise. This is because the classic methods were already calibrated using data from other case studies without any degree of freedom, whereas the used black box methods in this study were calibrated using observed data from the case study. The CNR higher performance among the classical models may be associated to the fact that, it classifies the traffic into sub categories which this study also proves this issue.

Figure 23

Scatter plots between observed and computed noise levels in calibration step by a) FFNN, b) ANFIS, c) SVR and d) MLR and in verification step by e) FFNN, f) ANFIS, g) SVR and h) MLR models

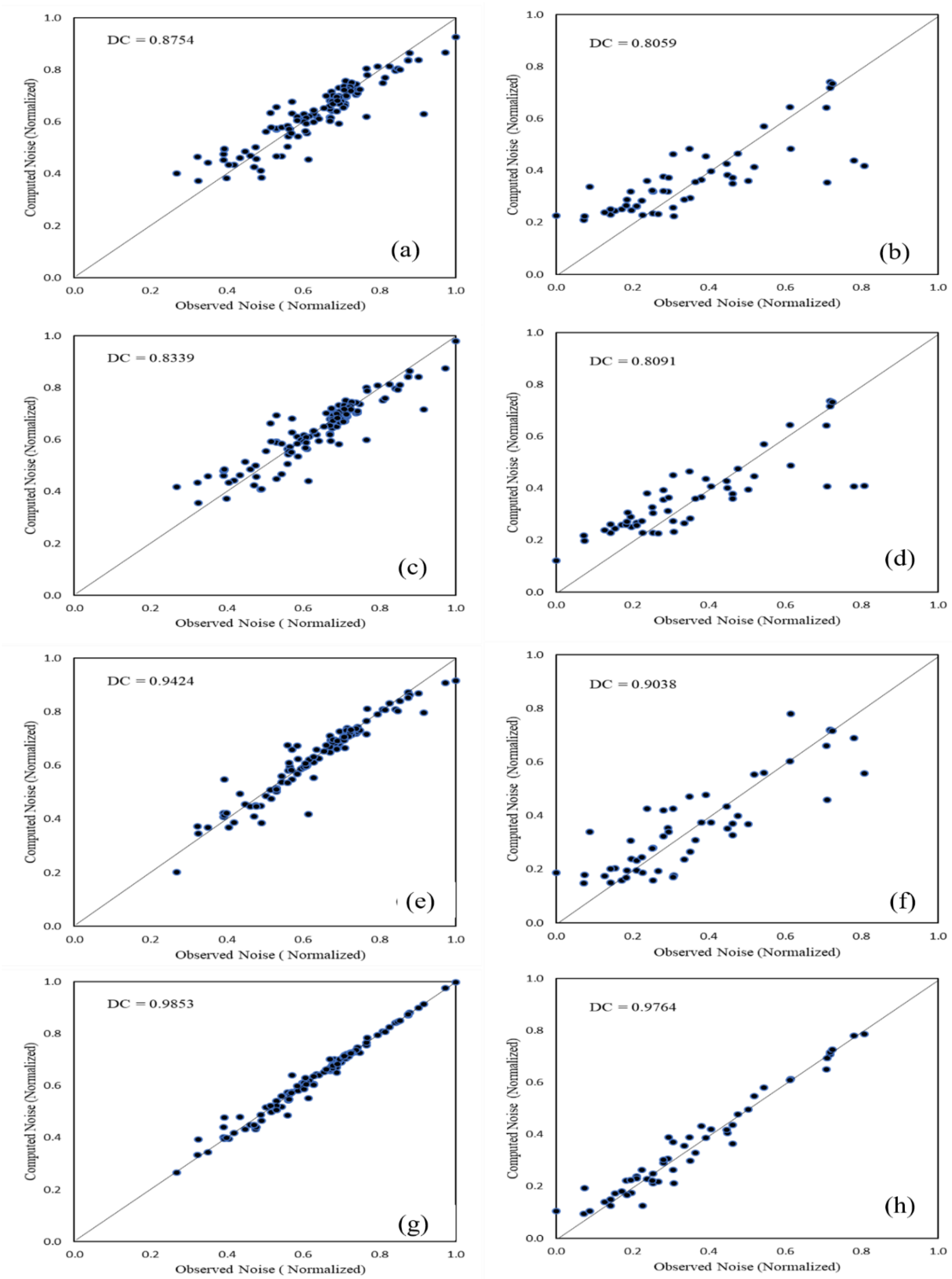


Ensemble technique

The two linear ensembles (SA and WA) have shown higher performance than the single models with the exception of the ANFIS model. This is attributed to the robustness of the ANFIS method possessed by combining the advantages of both fuzzy inference system and the ANN. It is also clear that linear averaging of numbers of a set always provides value lower than the highest value in the set. In the neural ensemble, the performances of the single models were increased by 3%, 12%, 14% and 24% for ANFIS, FFNN, SVR and MLR, respectively. The ANFIS ensemble improved the performance of the ANFIS, FFNN, SVR and MLR Single models by 11%, 19%, 21% and 31%, respectively. This shows that the nonlinear ensembles are more powerful in improving the performance of the nonlinear models. The efficiency of the ANFIS model over the AI-based techniques used in modelling nonlinear process was confirmed by the AE model. The scatter plots of the ensemble techniques in the calibration and verification stages are presented in Figure 24.

Figure 24

Scatter plots between observed and computed noise level in calibration step by a) SA, b) WA, c) NE and d) AE and in verification step by e) AE, f) WA, g) NE and h) AE techniques.



The RMSE value in the nonlinear ensemble techniques is also lower than that of the linear ensemble and Single models in both calibration and verification steps indicating error reduction in the ensemble techniques. The proposed ensemble technique as a data post-processing method parallelly processes the data using only a few data samples to enhance the prediction performance whereas for sophisticated models such as emotional ANN (Nourani, 2017) or deep learning ANN (Ma et al. 2017), large number of parameters and data samples are needed for model training.

Hybrid models

All the AI-based models led to reliable performance in the prediction of roadway traffic noise than the linear model (MLR). This is because, the AI based models have higher ability in modeling convoluted processes such as roadway traffic noise in addition to better generalization ability than the linear models (Nourani et al. 2019c). It can be seen that, the BRT model outperformed all other models used in this study in the prediction of the road noise by providing higher NSE value and lowest error (RMSE, MAE) at verification stage. Comparing the performances of the AI-based models with the MLR model indicated that, the BRT model has an improved prediction accuracy over the MLR model by up to 20.9% in the verification step, GPR up to 16.9%, FFNN up to 12.6% and lastly the SVR model which has an improved performance over the linear model by 10.3%. The BRT demonstrated higher prediction capability than GPR, FFNN and SVR models at both calibration and verification stages with NSE, RMSE and MAE values of 0.8679, 0.0852, 0.0626 respectively, at the verification stage. The ability of the BRT to model with high accuracy comes by ensemble of different regression tress and its ability to fit complex nonlinear relationships and automatically addressing the interaction effects between the predictions.

The results shown in Figure 25 show that the BRT fits the data better than all other models in verification stage. The data are more compacted along the diagonal line better than the other models which indicates better goodness of fit than other data driven models. Followed by the BRT is the GPR model, even though this is the first study to apply GPR model in vehicular traffic noise prediction, a similar outcome where GPR outperformed

ANN, SVR, and POD was also reported by Athavale et al., (2019) in a study to compare the prediction capability of different data driven models for temperature time series prediction. The GPR gets its high prediction ability from its flexibility to provide uncertainty representation (Cai et al. 2020). In terms of the model's accuracy, the FFNN model was more accurate than all other data driven models with least percentage increase in the NSE values between the calibration and verification stages, followed by the GPR model. Contrary to the findings by the Fan et al., (2018) where SVR was found to be more stable than the tree-based ensemble algorithms in the prediction of daily evapotranspiration, the SVR was found to be least stable for prediction of roadway traffic noise. The efficiency of the different models (with regards to NSE values) in both calibration and validation stages were compared by radar charts as shown in Figure 26. In addition to the radar chart, Taylor diagram was also used to compare the models' performances (see Figure 27). The Taylor diagram compares different statistical performance metrics (RMSE, correlation and the standard deviation) of the models. The azimuthal position on the Taylor diagram represents the correlation between the actual and calculated values. The gap between the observed and predicted fields with the same unit as the standard deviation has direct proportionality with the RMSE values. The value of the RMSE decreases as the correlation increases. With increasing radial distance measured from the origin, the pattern's standard deviation rises (Taylor 2001). When the correlation coefficient of a model is 1, it is considered to be a perfect model by reference point (Yaseen et al. 2018). If the calculated values' standard deviation is higher than the observed values' standard deviation, overestimation may occur, and vice versa. In the Taylor diagram, the azimuthal position gives the correlation between the actual and the computed values. The RMSE values are directly proportional to the distance between the observed and the predicted fields having same unit with the standard deviation. For any increase in correlation, the value of the RMSE is decreased. The standard deviation of the pattern increases with increasing radial distance measured from the origin. A model is said to be a perfect model by reference point when its correlation coefficient is 1. If the standard deviation of the computed values is greater than the standard deviation of the measured values, then it may lead to overestimation and vice versa.

However, considering the rRMSE values of the models at the verification stage (>20%), it shows that all models have fair performance with the exception of the BRT model which led to almost good performance. It is clear that, there is a need to improve the modelling performance of the process. To this end, the following hybrid models were for prediction of the roadway traffic noise.

Figure 25

Scatter plots of observed and computed roadway traffic noise levels in verification stage obtained by a) FFNN, b) SVR, c) BRT d) GPR and e) MLR

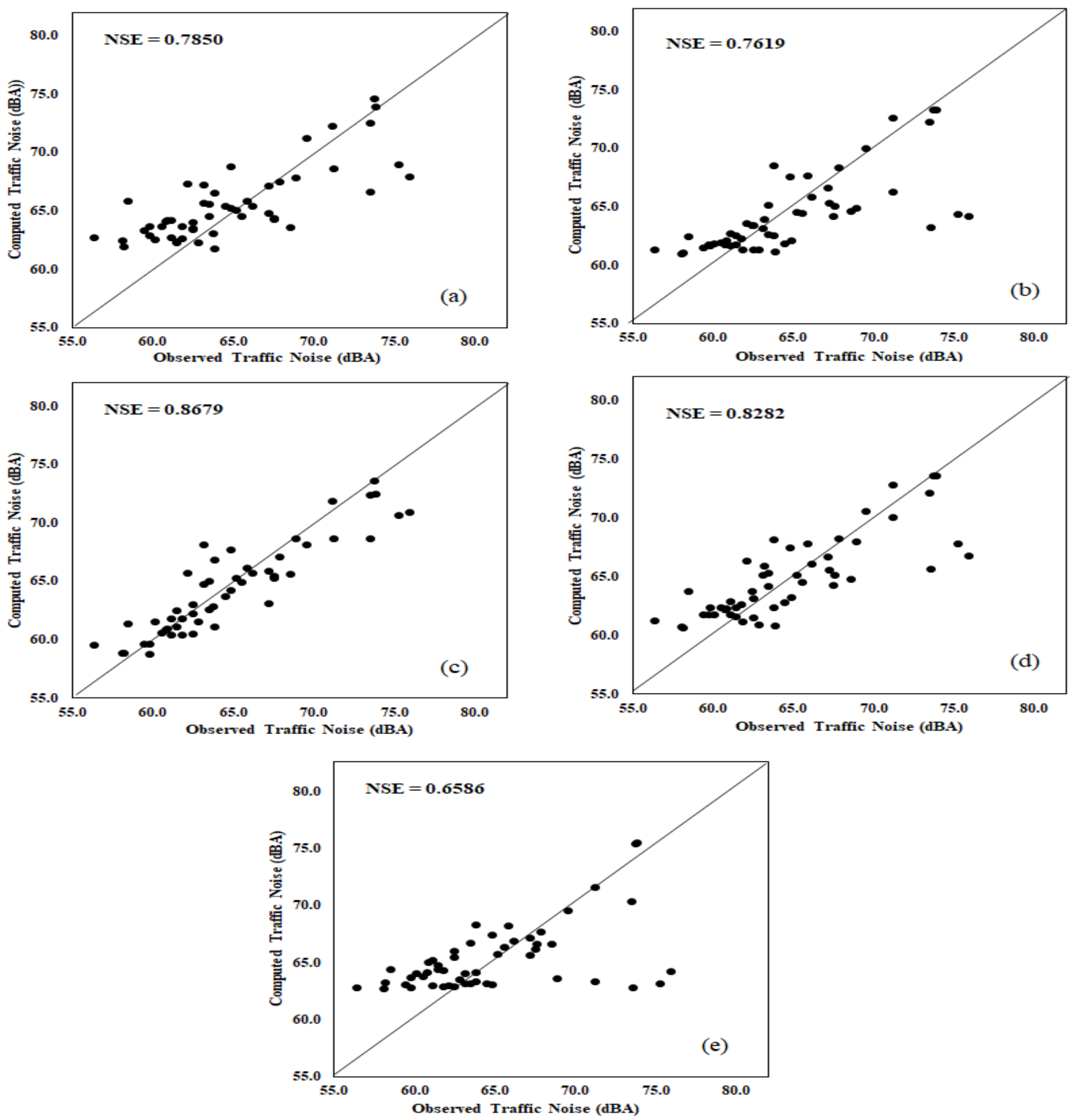


Figure 26

Radar Plot showing NSE values for different models in calibration and verification stages

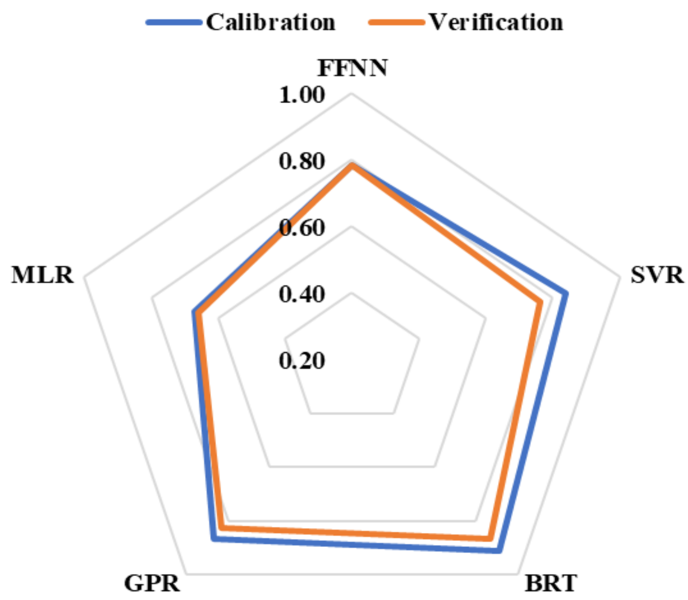
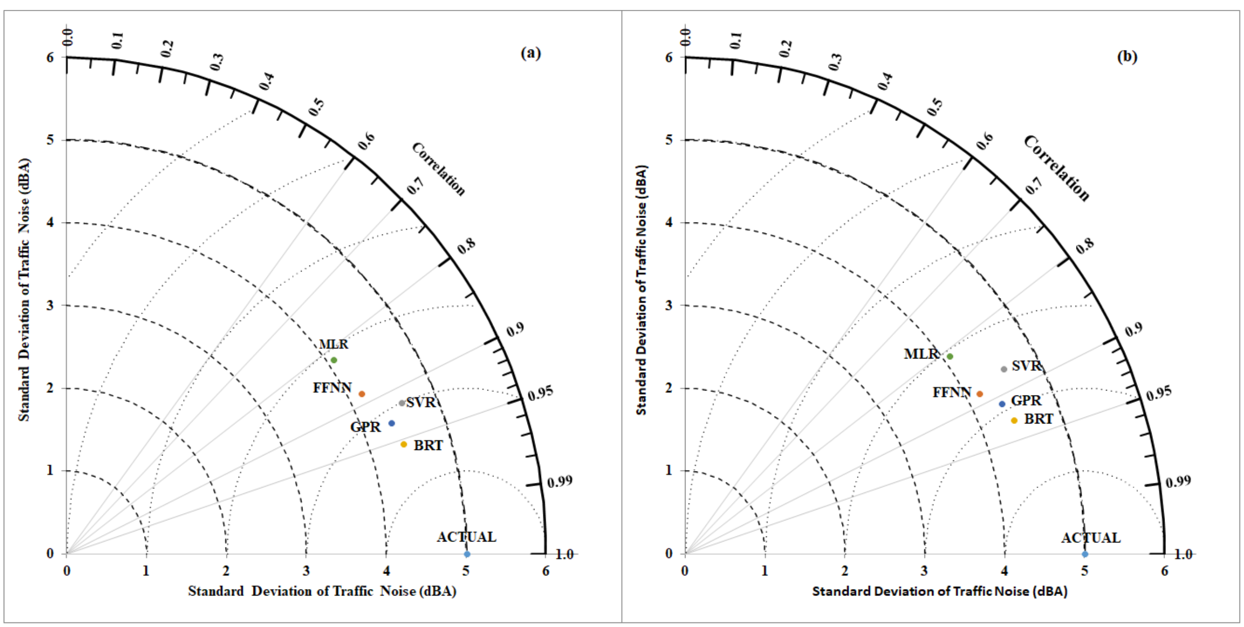


Figure 27

Taylor diagram representing different statistical parameters of the models in steps of (a) Calibration (b) Verification



The results of the hybrid models demonstrated increased performance in the prediction of roadway traffic noise with regard to the single models. Similar results were obtained by Nourani et al., (2011) where SARIMAX (Seasonal Auto Regressive Integrated Moving Average with exogenous input)-ANN model outperformed both SARIMAX and ANN models in daily and monthly rainfall-runoff modelling at both calibration and verification stages. Zhang et al., (2019) also found that linear-nonlinear hybrid (autoregressive integrated moving average (ARIMA)-SVR) could model emergency patient flow with higher accuracy in terms of MAPE, MAE, and RMSE than both the ARIMA (linear) and the SVR (nonlinear) models. The MLR-GPR model demonstrated higher performance at the verification stage than all linear-nonlinear hybrid models with NSE value of 0.9312, followed by MLR-BRT (0.9100), then MLR-FFNN (0.8845) and finally MLR-SVR (0.8723). Performance evaluation of the linear-nonlinear hybrid models using the rRMSE showed that, all the hybrid models have excellent to good performance with MLR-GPR having the highest accuracy with rRMSE value of 7.4% (excellent). Table 11 clearly indicates that the hybrid modelling improved the performance of the nonlinear models by up to 10.30% for the AI models and up to 27.26% for linear models. The predictive performance of the hybrid models is presented graphically using the Taylor diagram (see Figure 28) and Radar plots (Figure 29). It can be seen clearly that, the MLR-GPR hybrid model was the best model outperforming all single and linear-nonlinear hybrid models. Comparing the absolute error of the hybrid models in the roadway traffic noise prediction using the box plot in Figure 30 revealed higher accuracy of the MLR-GPR hybrid model. The MLR-GPR model has the least forecasted mean absolute error (0.85 dBA) than all the hybrid models, making it reliable for the estimation of roadway traffic noise. As a result, the hybrid model could be used for enhancing the performance of the non-linear models. The results from the hybrid models could be integrated for development of a more accurate and reliable traffic noise maps that will in turn help the stakeholders in providing a sustainable mitigation measure for reducing the peoples' incessant exposure to the traffic noise. The use of pavement materials with suitable textures during the construction, car sharing and the use of electric cars are some of the sustainable tools in providing a noise healthy environment.

Figure 28

Taylor diagram representing different statistical parameters of the hybrid models in steps (a) Calibration (b) Verification

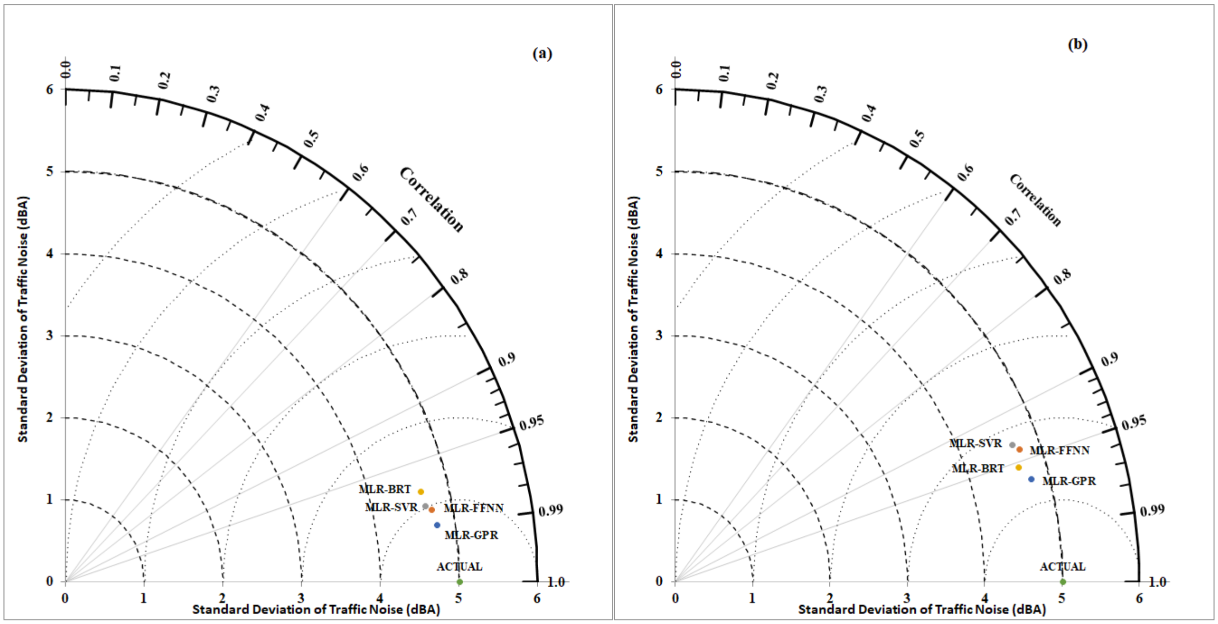


Figure 29

Radar Plot showing NSE values for the hybrid models in calibration and verification stage

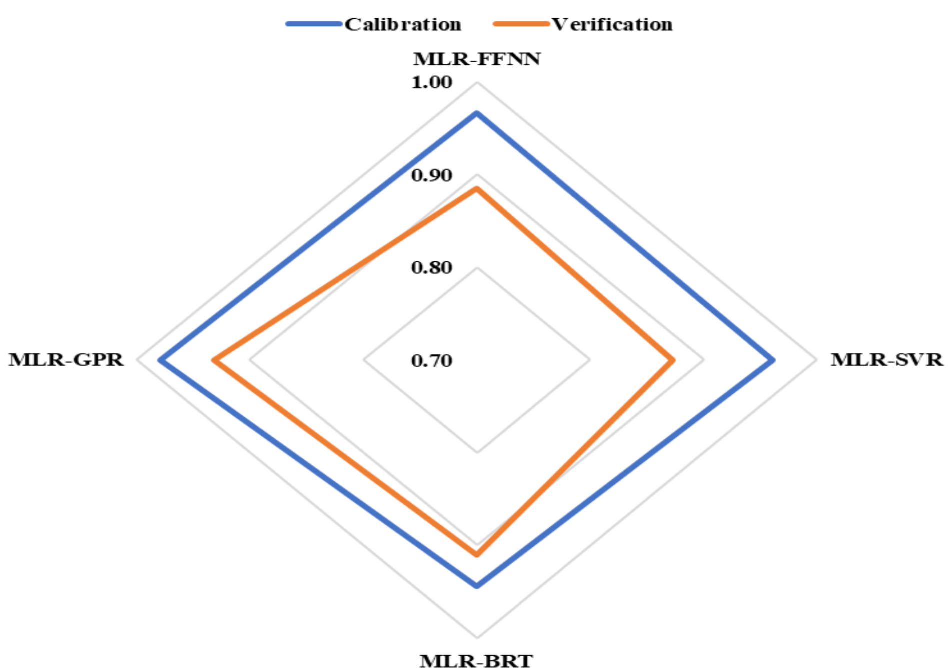
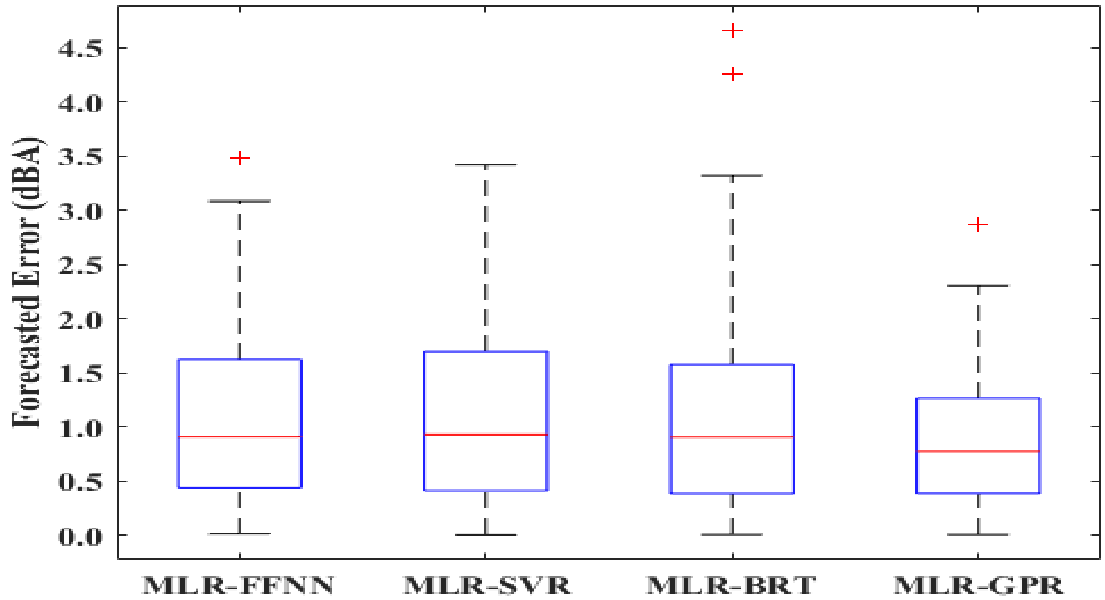


Figure 30

Boxplot for the absolute forecasted error in the prediction of the traffic noise by the hybrid models



EANN model

The results of the models in Scenario 1 with vehicle classification (C, MV, HV) and V as input variables led to higher performance than the model in Scenario 2, which uses Q, P and V as input parameters. Feeding the classes of the vehicles into the models improved the performance of the model in the verification stage up to 12% for FFNN and 8% for the EANN models. The result is expected since two of the parameters in Scenario 2 (P and V) were ranked least among the factors impacting the road traffic noise in the study area even though Q was ranked as the most relevant factor to the noise level. Different vehicles emit different levels of noise and the performance of the AI model depends on the careful selection of the relevant input parameters (Nourani et al. 2019c). It is clear that even with the less relevant input parameters (in Scenario 2), the EANN was able to achieve high performance (0.7321), which is higher than that of the FFNN model DC (0.7167) with more relevant factors (Scenario 1). This indicates the rigorous nature of the EANN in modelling vehicular traffic noise. Since the EANN could better understand the variations in the data due to the presence of emotional hormones, the performance increase in the model performance between Scenarios 1 and 2 was relatively small (8%) compared to that of the FFNN model (12%).

For a more comprehensive presentation of the performance of the EANN model in the estimation of the traffic noise for the two considered scenarios, a Taylor presentation diagram (Figure 33) was developed to show how close the predicted value is to the measured value by considering the correlation, standard deviation and RMSE between the measured and estimated traffic noise levels. In the Taylor diagram, the standard deviation of the pattern is proportional to the radial measured from the origin, the correlation between the two fields is given by the azimuthal position of the test field and the centered RMSE value is proportional to the distance between the actual and the estimated fields with the same units as the standard deviation (Taylor 2001). The value of the RMSE decreases with an increase in correlation. A perfect model is set apart by the reference point with the correlation coefficient equivalent to 1, and a similar abundancy of varieties contrasted with the observations (Yaseen et al. 2018). From the result shown in Figure 33, it can be clearly seen that the EANN model demonstrated higher capability than the FFNN for the estimation of the traffic noise level of Nicosia for two scenarios in terms of RMSE and pattern correlation.

Although, some pre and post-processing techniques such as multi-model ensemble (Nourani et al. 2019b) and clustering techniques (Baghanam et al. 2019) have been already applied to enhance the prediction accuracy of FFNN, such post/preprocessing methods are done mostly outside the framework of ANN model and requires extra knowledge. However, adding some few emotional hormones to the classic FFNN could provide better result in traffic noise modeling without the need for some data preprocessing operations outside the ANN framework.

Also, comparing the performance of both EANN and FFNN models with the results of MLR revealed the superiority of the AI models over the MLR in the prediction of road traffic noise for both Scenarios 1 and 2 (see Table 4.10). The performance of the EANN in comparison to the MLR model was improved by almost 35% for both Scenarios 1 and 2. For FFNN, the model performance was improved by 26% and 22% for Scenarios

1 and 2, respectively. The scatter plots for the EANN and the FFNN models for both Scenarios 1 and 2 are given in Figures 31 and 32, respectively. The performance of the EANN and FFNN models in the estimation of the road traffic noise was further evaluated in comparison with some empirical models. RLS90, CNR, and the Burgess models were the empirical models used for the contrast. The RLS90 model was developed in Germany and is still the most relevant empirical model in the country. The equivalent noise level at 25m from the noise source under idealized traffic condition is expressed as the function of the traffic flow and percentage of heavy vehicles. The CNR model was developed by the Italian “Consiglio Nazionale Delle Ricerche” by modifying the German RLS90 model. In the CNR model, the traffic is categorized into subcategories taking into account their different acoustic contributions to the overall traffic noise level (Garg and Maji, 2014). The first application of the Burgess model was in Sydney, Australia. The model expresses the noise level as a function of traffic flow, distance of the source from the receiver and percentage of heavy vehicles in the traffic (Quartieri et al., 2009). The performances of the empirical models are summarized and presented in Table 18.

Table 18

Results of the applied empirical models

Models	DC	RMSE dB(A)
RLS90	0.1268	4.6826
BURGESS	0.3580	4.0150
CNR	0.4342	3.7693

*RMSE has no unit, normalized data

The results of the AI-based models in Table 12 were compared with those of the empirical models presented in Table 18. Results of the comparison indicated that the AI-based models estimated the road traffic noise with higher precision than the empirical models, which is due to the ability of the AI models to learn from samples where physical relationships between the inputs and the outputs are not known as in the case of vehicular traffic noise. The empirical models performed poorly in Nicosia, North Cyprus because they were already standardized with data from different case studies with different traffic compositions and characteristics lacking some degree of freedom, while the AI models considered in this research were trained with experimental data from the current case study. The CNR model demonstrated higher efficiency than the other two empirical models, which may be related to the fact that it categorizes the traffic into subcategories, which this study also proved using AI models to improve estimation accuracy.

Figure 31

Scatter plots for Scenario 1 in the verification stage (a) FFNN (b) EANN

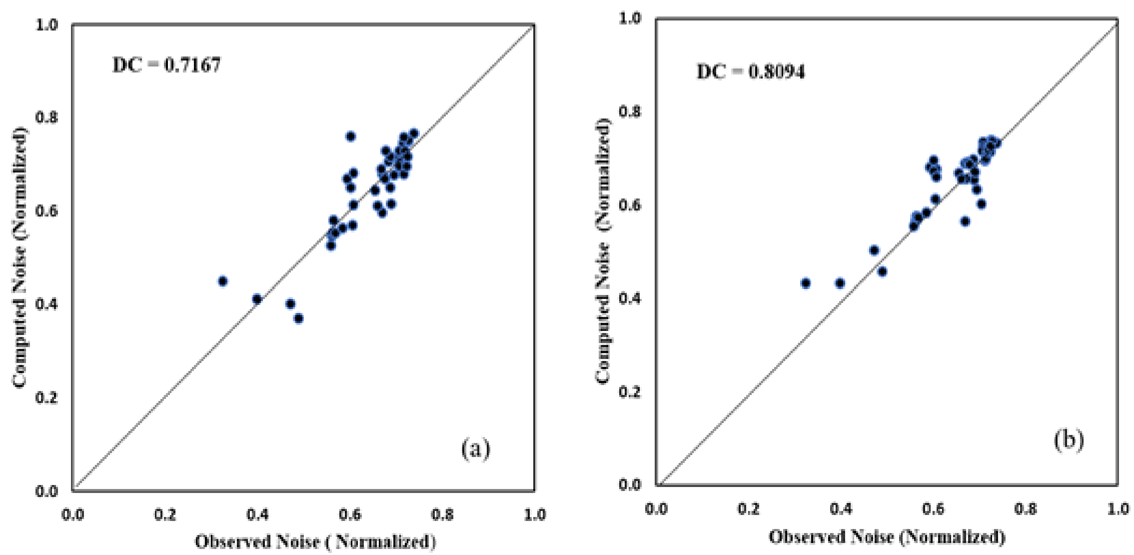


Figure 32

Scatter plot for Scenario 2 in the verification stage (a) FFNN (b) EANN

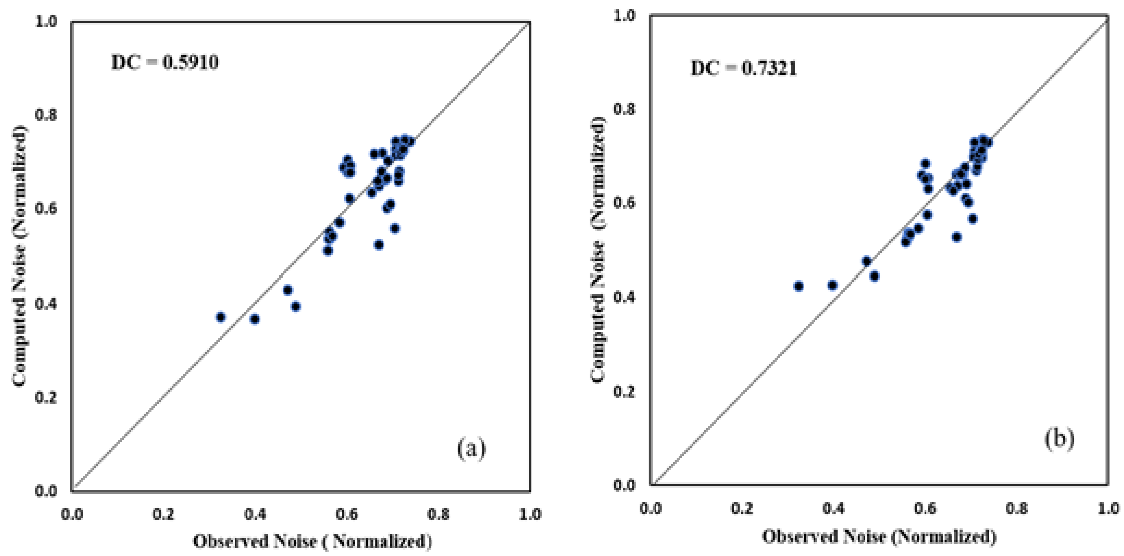
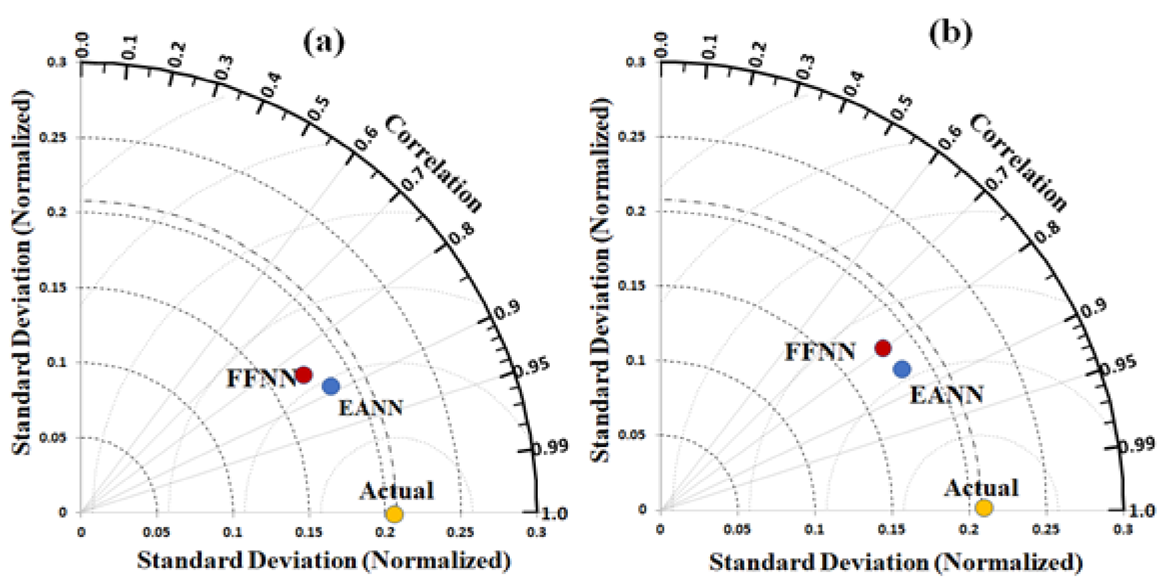


Figure 33

Normalized Taylor diagram displaying differences within pattern statistics of computed values (a) Scenario 1 (b) Scenario 2.



Traffic noise-air pollution interactions

Recently, the combined exposure effect of air and noise pollution on human health and their spatial relationship have begun to attract the attention of researchers (Khan et al. 2018). For example, Khan et al., (2020) studied the spatial relationship between the traffic related air and noise pollution in two cities and found the air-noise correlation to be between 0.01 and 0.42. For the first time, Lin et al., (2018) used noise level, canyon index and meteorological parameters as input parameters for predicting the ultrafine particles concentration and the result provides a good result with a determination coefficient of 0.77. Danciulescu and Bucur, (2015) found a good correlation between the traffic noise and air pollutants concentration. The study also highlighted noise level as an indicator of high air pollution. A strong correlation between noise level and three air pollutants (Nitrogen dioxide and PAH) in urban parks had been obtained in a study by Klingberg et al., (2017). Medina-ramo et al., (2011) found a strong correlation of 0.62 between nitrogen dioxide and equivalent noise level (L_{24h}) in Girona town, Spain. Gan et al., (2012) modelled population exposure to noise and air pollution in large metropolitan. The result of the study found that, the modelled traffic noise has weak correlation with land use regression estimates of traffic-related air pollutants including black carbon, particulate matter with aerodynamic $PM_{2.5}$, NO_2 and NO. The highest correlation was with black carbon (r=0.48), whereas the lowest correlation was with $PM_{2.5}$ (r=0.18).

For determining the interaction between air pollutants and traffic noise in this study, $PM_{2.5}$ was selected as the air pollutant to be used. This is because $PM_{2.5}$ acts as the major indicator for air quality monitor system (Donkelaar et al. 2006) and 64% of the $PM_{2.5}$ was reported to come from the vehicular traffic (European Environment Agency 2012). Also, both traffic noise and $PM_{2.5}$ are mostly generated by traffic flow and increased with increasing traffic volume (Nourani et al. 2020a).

Air pollutants in M1 model were found to predict the $PM_{2.5}$ with higher prediction accuracy than meteorological parameters and the traffic data with an NSE value of 0.7620 in the training stage and PBIAS value of 0.4218 in the verification stage. The meteorological parameters modelled PM2.5 with better accuracy in the testing stage showing that, air pollution is significantly influenced by weather conditions. The M3 which is the model with traffic data as its input parameters was the least to predict $PM_{2.5}$ with poor NSE coefficient of 0.2116 in the verification stage which is unsatisfactory (NSE<0.5) based on the ranking given by Moriasi et al. (2007). Combining the three sets of the data as in M4 shows a significant increase in the NSE value (0.8118) and decrease in RMSE in the verification stage compared to the models M1-3. Combining the three sets of input parameters in M4 has improved the performance accuracy of M1, M2, M3 by 19%, 14%, 60%, respectively in the verification stage. Also, from Figure 34 (training stage) and Figure 35 (verification stage), the data is more compacted along the bisector lines of the charts for M4 indicating better goodness of fit when all the parameters were used to predict the concentration of $PM_{2.5}$ in the atmosphere.

Figure 34

Scatter plots between computed and Pm2.5 concentration in the training stage for a) M1, b) M2 and c) M3 d) M4.

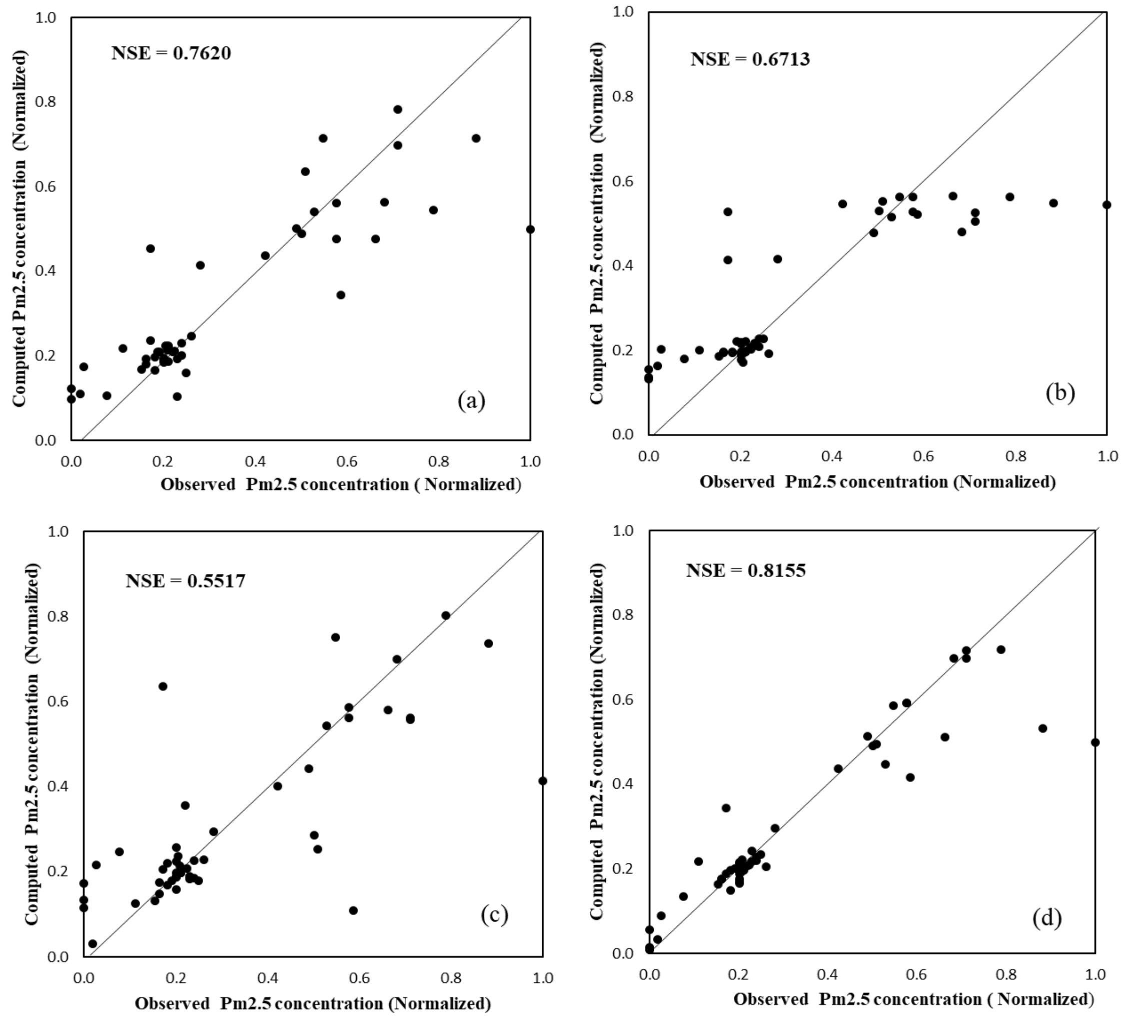
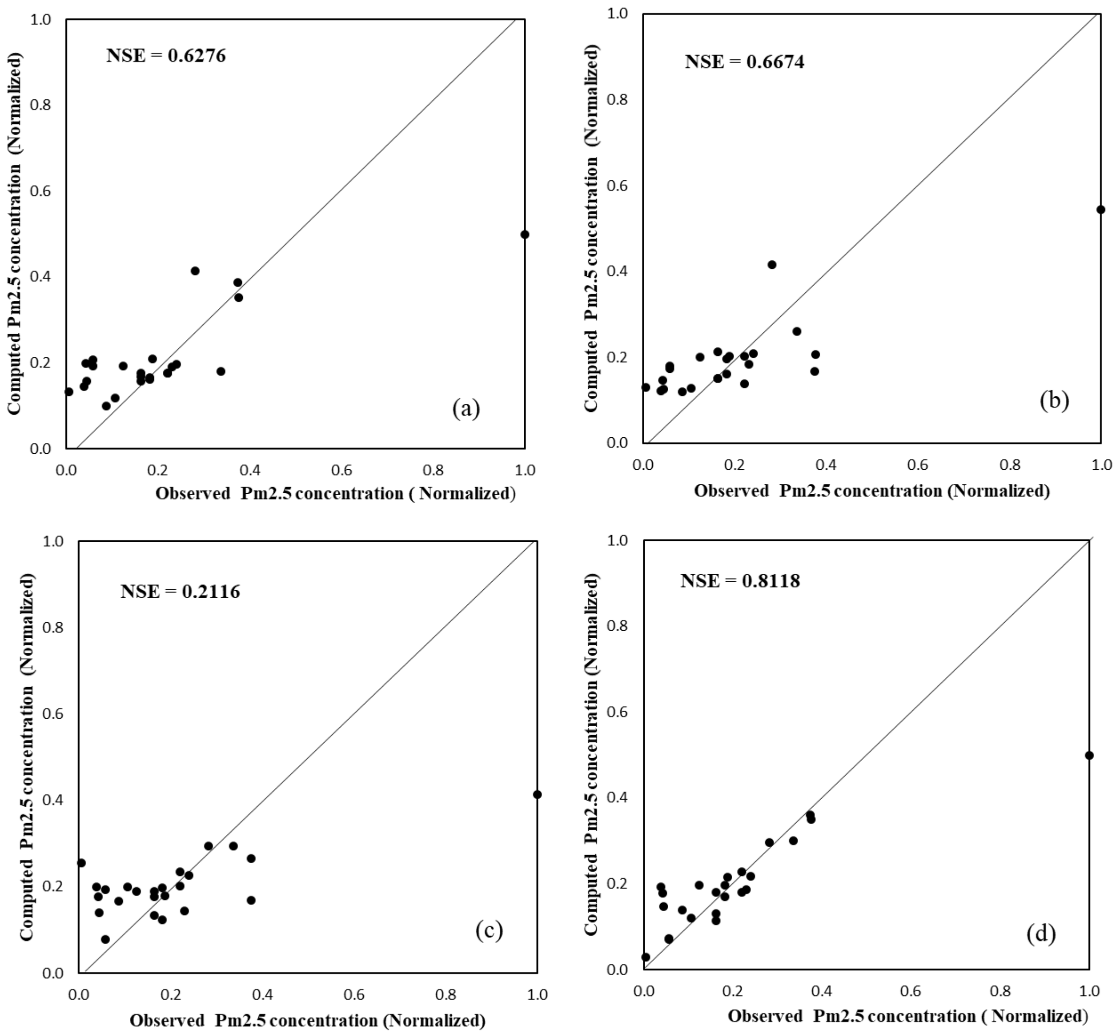


Figure 35

Scatter plots between computed and Pm2.5 concentration in the verification stage for a) M1, b) M2 and c) M3 d) M4.



In scenario II, four models (N1-4) were also developed to model the $PM_{2.5}$ and the result was presented in Table 18. It can be seen that N1 which uses the air pollutants and traffic noise as input parameters model the $PM_{2.5}$ with higher prediction accuracy than the models developed using meteorological parameters (N2) and traffic data (N3) as inputs with NSE and RMSE values of 0.7399 and 0.0810, respectively in the verification stage. The N4 model which combined all the three groups of datasets and the traffic noise gave higher prediction accuracy than all the models with single group as input variables.

Combining all the data in the N4 models has improved the performance of N1, N2 and N3 models by 12%, 16% and 19%, respectively in the verification stage. The models' goodness fit in the training and verification stages were presented in Figure 36 and Figure 37, respectively. It can be clearly observed that the data is more compacted along the bisector line for the N4 model in both training and verification stage.

The result of the group sensitivity analysis has demonstrated higher relevance of the air pollutants followed by the meteorological parameters and lastly the traffic data. The result also indicated that inclusion of traffic noise into $PM_{2.5}$ (N1-4) could improve the performance could increase the performance of M1, M2, M3 and M4 for the prediction of $PM_{2.5}$ by up to 11.23%, 2.17%, 36.54%, 5.24%, respectively in the verification stage. Figure 38 was used to compare the performance of al the models N1-4 and M1-4 using the Taylor diagram.

Figure 36

Scatter plots between computed and Pm2.5 concentration in the training stage for a) N1, b) N2 and c) N3 d) N4.

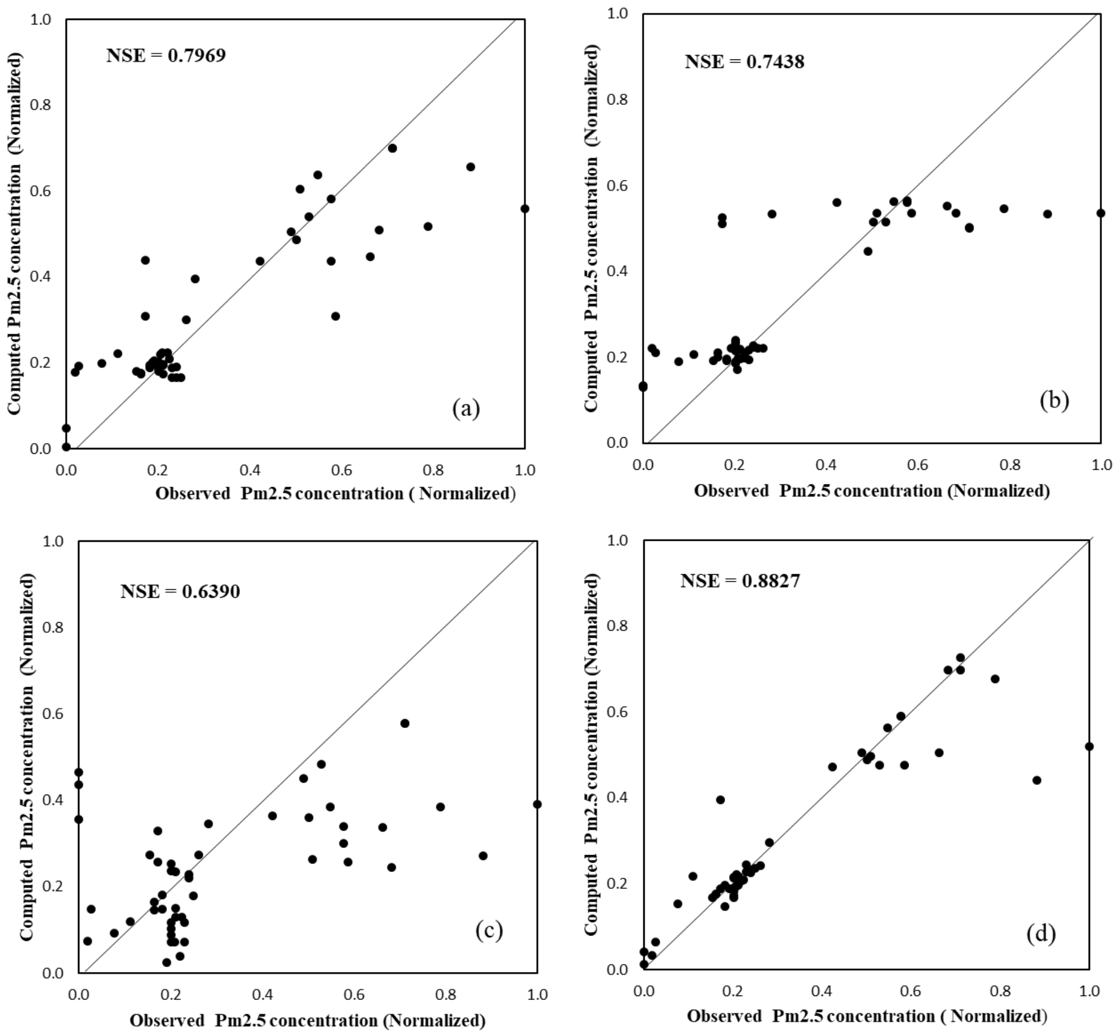


Figure 37

Scatter plots between computed and Pm$_{2.5}$ concentration in the verification stage for a) N1, b) N2 and c) N3 d) N4.

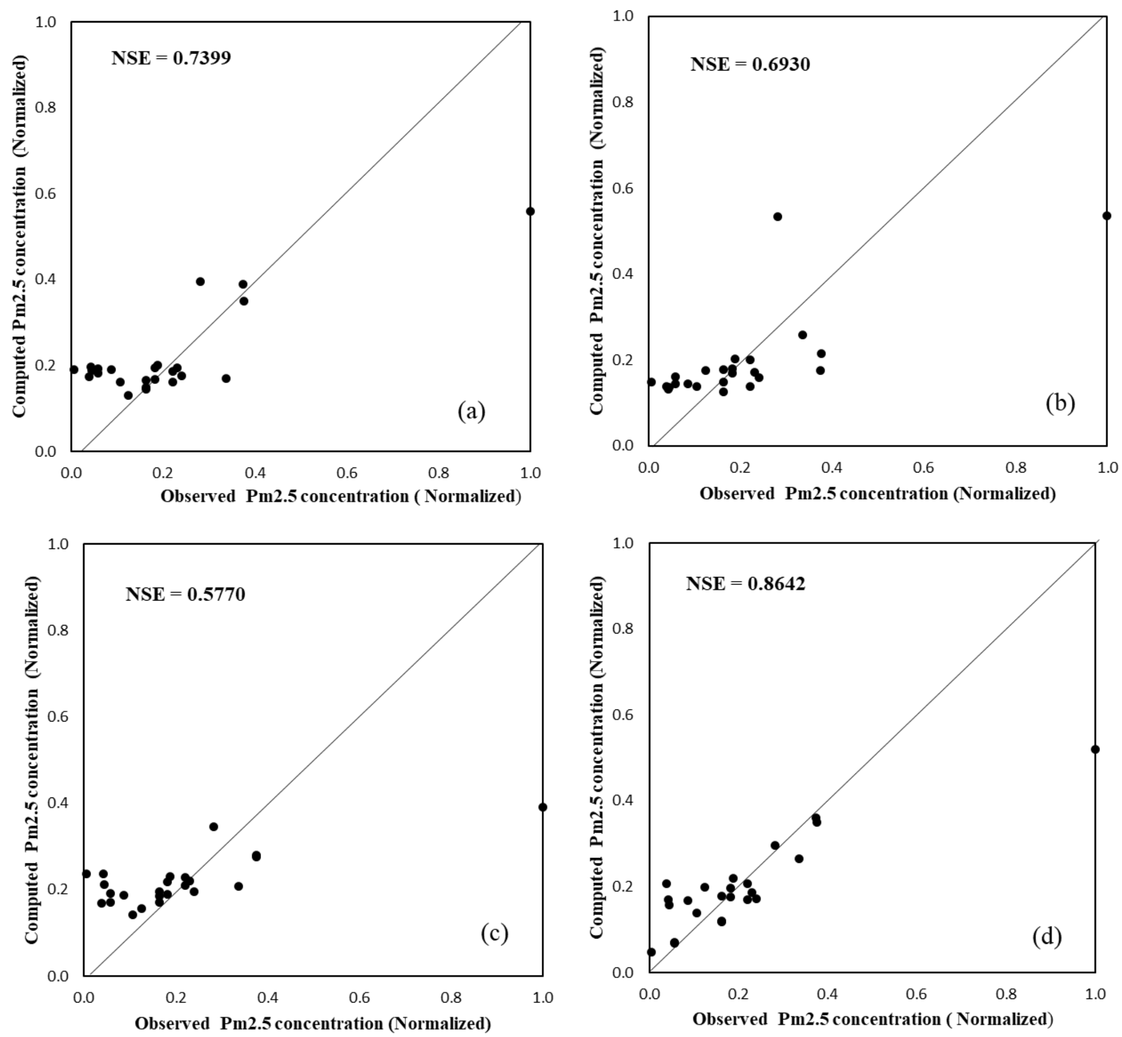
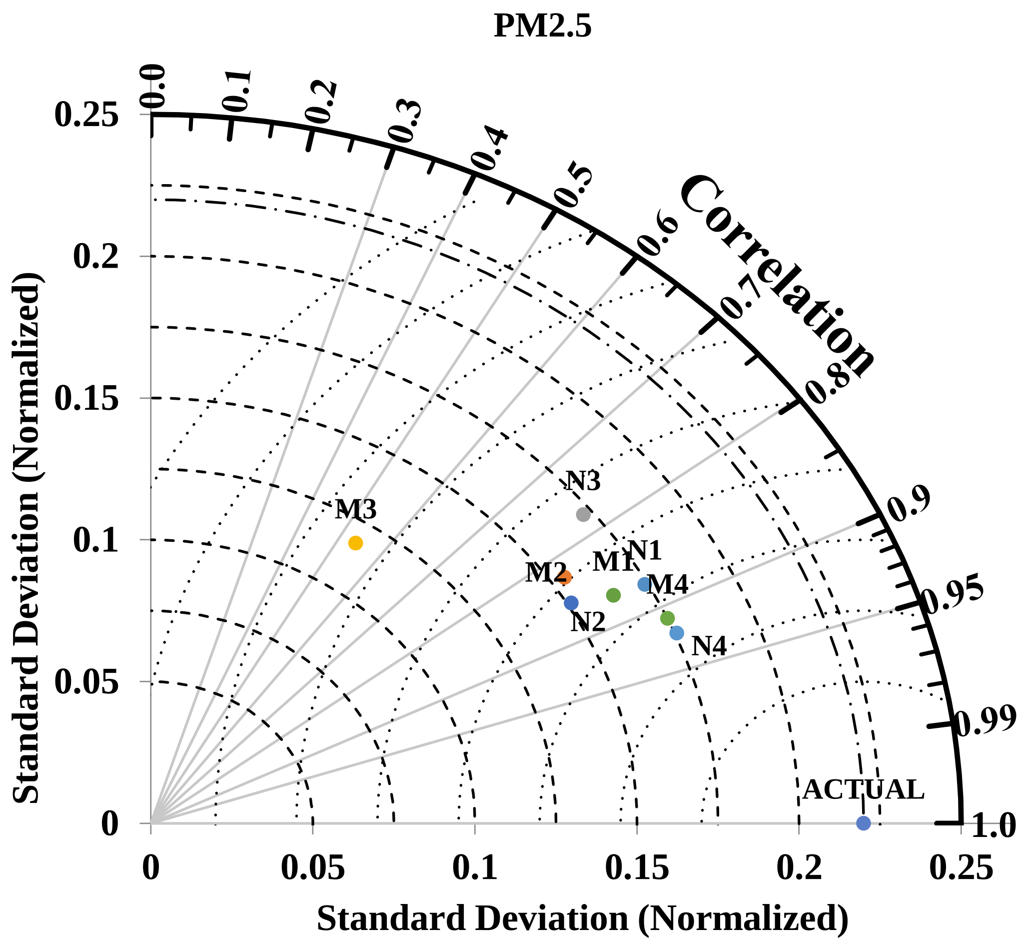


Figure 38

Taylor diagram comparing the performance of the developed models



Furthermore, for comparing the performance of the SVR is the prediction of the $PM_{2.5}$ with other models, two additional models using the FFNN and MLR were developed with the combined inputs parameters in scenario II which were found to be more effective in $Pm_{2.5}$ predictions. Several models of the FFNN models were developed by changing the modelling structure. The optimum FFNN model was obtained with 13-16-1 structure trained with Levenberg-Marquardt algorithms at 50 epochs. The results were shown in Table 19. It was seen that both FFNN and MLR predicted the $PM_{2.5}$ with good accuracy (NSE > 0.65). However, from the comparative result, it was obvious that the SVR model predict the $PM_{2.5}$ with higher accuracy (NSE =0.8642). The SVR improved performance accuracy of the FFNN and the MLR model in the verification stage by 5% and 14%, respectively. Findings from the study indicate that SVR performed better in predicting $PM_{2.5}$ the study area than the three data driven models used. The MLR gives the least NSE value since it only captures the linear pattern in the leaving the nonlinear relationship uncaptured.

In the last stage of the modelling, an ensemble approach was used by combining the outputs the two nonlinear models and the linear model. SVR kernel was used for obtaining the ensemble output of the three models. SVR kernel was used for the ensemble considering its superiority over the FFNN and MLR in the base modelling. The techniques combine the unique features of the individual models (linear and nonlinear strength) hence improving prediction accuracy. The study applies only the nonlinear ensemble since studies by Nourani et al. (2020a) mentioned that, only nonlinear ensembles improves prediction accuracy as linear averaging provides values less than that of the best base model. Th results shows that the ensemble approach (SVR-E) improved the prediction accuracy in both training and verification stage. The SVR-E could improve the performance accuracy of the SVR, FFNN and MLR models by 3%, 8% and 17%, respectively in the verification stage. For a clearer comparison of the ensemble model, a radar plot (Figure 39) was used to compare the NSE values of the SVR-E and the other three single models with all parameters as input parameters

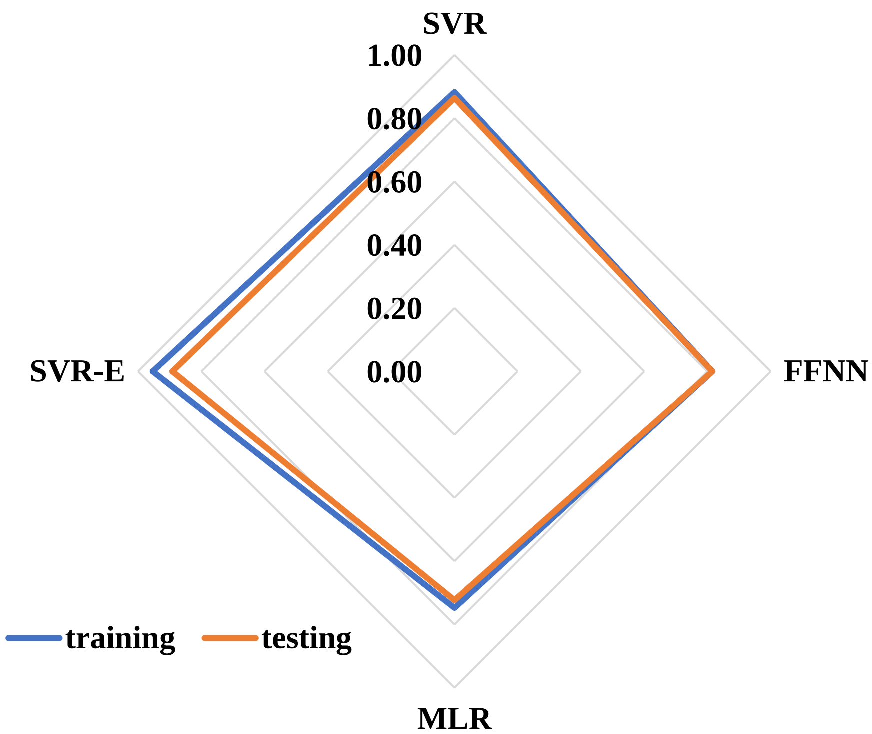
Table 19

Comparison between SVR, FFNN, MLR modelling results and the ensemble model for $PM_{2.5}$ prediction

MODELS	Inputs	NSE	RMSE	R	PBIAS	NSE	RMSE	R	PBIAS
		Training				Verification			
SVR	All	0.8827	0.0577	0.8536	0.2572	0.8642	0.0993	0.9207	0.1509
FFNN	All	0.8159	0.1047	0.9007	0.2096	0.8156	0.0645	0.7895	0.3352
MLR	All	0.7476	0.1225	0.8593	0.2561	0.7233	0.0791	0.6786	0.3759
SVR-E	All	0.9535	0.0526	0.9756	0.0836	0.8914	0.0539	0.8682	0.2240

Figure 39

Comparing the NSE values of SVR, FFNN, MLR modelling results and the ensemble model for $PM_{2.5}$ prediction



Chapter V Summary

The chapter discussed the results and findings of the study with other studies in the literature. It was found that the proposed models developed in the study provide higher prediction accuracy than the single AI-based models with the ensemble model been the most promising. It was also found that all the potential input parameters to the traffic noise models have a direct proportionality with traffic noise except the percentage of heavy vehicles which has an inverse proportionality at higher value. Likewise, inclusion of traffic noise in modelling the $Pm_{2.5}$ improved models' performance.

CHAPTER VI

Conclusions and Recommendations

Conclusions

Vehicular Traffic noise in Nicosia

In this study, the traffic noise level of Nicosia city was studied and modelled using single AI-based models (ANFIS, FFNN, SVR, GPR, BRT), conventional MLR method and some empirical models (CNR, RLS90 and BURGESS). The traffic noise in the study area is high with an average value of 69.74 dBA. The noise level in the study area is higher in the evening, followed by morning hours. The lowest noise level was observed during the afternoon observation. The residents along the major arterials and expressway in the study area are exposed to high noise level for the morning and evening hours. Proper measures are therefore required to reduce the effect of noise exposures in the affected areas. However, employing the use of suitable pavement texture during construction could provide a more cost-effective way of reducing vehicular traffic noise which in turn reduces the adverse health effect of the traffic noise.

Prior to the development of the noise models, a nonlinear sensitivity analysis was performed for the selection of dominant noise traffic predictors for the study area. The number of cars, van/pickup, trucks, buses and average speed were found to be the most relevant factors contributing to traffic noise with the number of motorcycles and horns having a low contribution to the noise level. The fewer number and low range in the number of motorcycles in the traffic stream and horns at the observation points are the possible reasons why their relevance was not noticed in the study area. It was observed that all of the inputs have a positive nonlinear relationship with the noise level except P, which has a negative relationship at higher values (>5%), which was due to the inverse relationship between HV and the road capacity (Chandra et al. 2016). The traffic noise level increased significantly with increases in Q and C at lower traffic volumes (<600veh), but at higher values, the noise increased slightly with increases in the Q and C. Also, at lower V values (<40kmph), the noise tended to increase significantly, and then slowly when V value was high (>40kmph).

Classifying the vehicles into different categories before feeding the traffic data into the AI models was observed to be helpful to improve the performance of the single models. Comparison of the obtained results by the single models proved that ANFIS has higher prediction capability than other models due to its robustness in dealing with uncertainties. Also, when compared with the result of the empirical models, the AI-based models were found to have higher accuracy and better estimation capability than the classical models in estimating traffic noise due to their ability in modelling complex and nonlinear process like traffic noise. Three novel models (ensemble, hybrid and EANN) were developed in this study for improving traffic noise prediction.

Subsequent to the development of the single black box models, four ensemble techniques combining the advantages of each of the single models were developed to enhance the performance of the Single models using the outputs of the single models as input variables to the ensemble techniques. The ensemble techniques improved the performance of the single models in the prediction of the noise levels with nonlinear ensemble techniques exhibiting higher performance due to their robustness in dealing with complex processes such as traffic noise. AE was found to be the most robust technique by improving the performance of ANFIS, FFNN, SVR, MLR and the classical models in the verification stage by 11%, 19%, 21%, 31%, and 57%, respectively. The efficiency of the linear ensemble techniques outperformed that of the single models except for the ANFIS model which was the best among the single models since linear average always provides result lower than the maximum value in the set.

In the hybrid modelling, four linear-nonlinear hybrid models were applied for improving the performance of the single models. Performance evaluation of the hybrid models using NSE, RMSE, MAE and rRMSE indicated that, the hybrid models demonstrated higher prediction capability than their equivalent single models with hierarchical order of MLR-GPR > MLR-BRT > MLR-FFNN > MLR-SVR. The MLR-GPR hybrid model improved the efficiency of the MLR and GPR models in the verification stage up to 27.26% and 10.30%, respectively. This shows that for the prediction of roadway traffic noise, stronger nonlinear models performed better when incorporated with linear models. The result of this study can be useful for the stakeholders in predicting noise level across the Nicosia which could further be used in developing noise maps with higher accuracy.

The efficiency of the EANN model over the classical FFNN was evaluated using two input scenarios. In the first scenario, C, MV, HV and V were used as the models' inputs. In the second scenario, the input parameters considered were Q, P and V. Application of the EANN model was found to improve the efficiency of the classical FFNN model up to 9% and 14% in the verification stage for Scenarios 1 and 2, respectively. Also feeding the AI models with vehicular classification (cars, medium vehicles, heavy vehicles) could improve the performance of the AI models by 8% and 12% for EANN and FFNN, respectively. The AI models have demonstrated higher capability in the estimation of the traffic noise than both the conventional MLR and empirical models. Although EANN has demonstrated robustness over the FFNN in modelling the traffic noise with limited observed data, the application of EANN with a much larger dataset may provide better results with less error variance.

Relevance of traffic noise in $Pm_{2.5}$ prediction

In this study, the significance of using a traffic noise as an input parameter in the prediction of particulate matter $PM_{2.5}$ was evaluated. The dataset used for conducting the study contains air pollutants, meteorological parameters, traffic data and traffic noise level simultaneously collected from seven sampling points in North Cyprus. The average traffic noise in the study area was found to 69.74 dBA. Also, the average $PM_{2.5}$ concentration in the area is 5.28 ug/m^3 higher than the optimal level of 25 ug/m^3 recommended by WHO. The study found traffic noise to have a good correlation with $PM_{2.5}$ (R=0.57). Two modelling scenarios (I and II) were used in obtaining the relevance of adding traffic noise as an input variable for the prediction of $PM_{2.5}$ concentration in areas with high traffic noise. All the models developed in scenario -I does not contain traffic noise as input parameter while all models developed under scenario II had traffic noise as input variables in addition to other variables. The modelling results shows that, all models in scenario II demonstrated high prediction accuracy than the corresponding models with in scenario I by up to 12% in the verification stage indicating relevance of the traffic noise as an input parameter for the prediction of $PM_{2.5}$ in areas with high traffic noise. Modelling $PM_{2.5}$

with combined relevant input parameters of air pollutant, meteorological parameters, and traffic data could improve the performance of the model when only one set of the parameters was used up to 12, 17 and 29% for models containing only P, M and T respectively.

Recommendations

Recommendations According to Findings

Considering the results obtained in the study using the ensemble modelling, the following recommendations could be made:

- The traffic noise in the study area is high and therefore, sustainable mitigation measures that could reduce traffic noise such as the car sharing which will help reduce number of cars on the road should be implemented.
- The stakeholders and relevant authorities responsible for noise regulation of environmental noise could employ the use of AE ensemble approach for prediction of vehicular traffic noise as it provides 97% accuracy.
- In the air pollution predictions and assessment, traffic noise should be included as the result of the study indicates its relevance by up to 12% in the prediction of $Pm_{2.5}$.

Recommendations for Further Research

- Future studies could also employ other AI based models such as M5 model tree, random forest, genetic algorithm, multivariate adaptive regression splines, etc. as single models for ensemble modeling studies.
- Future studies could also apply ensemble technique by combining outputs of the empirical noise models.
- The data used in this study was obtained at straight tangents of the road which are reasonably far from intersections, future studies could study the traffic noise at intersections.
- The interaction between traffic noise and other traffic induced air pollutants such NO_2 and CO could also be explored.

Chapter VI Summary

From the study, it can be seen that both traffic noise and $Pm_{2.5}$ exceeds the recommended levels set by WHO. It can be concluded the ensemble of result of different models proposed in the study predicts the vehicular traffic noise with higher accuracy than both empirical, single AI-based and hybrid models. It can also be concluded that the traffic noise has strong correlation with $Pm_{2.5}$ in the city of Nicosia.

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APPENDICES

Appendix 1

Curriculum Vitae

PERSONAL INFORMATION

Surname, Name: Umar Ibrahim Khalil

Nationality: Nigerian

Date and Place of Birth: 15 October, 1987, Kano-Nigeria

Marital Status: Married

EDUCATION

Degree	Institution	Year of Graduation
M.Sc.	Atilim university, Department of Civil Engineering	2014
B.Sc.	BUK Department of Civil Engineering	2011

WORK EXPERIENCE

Year	Place	Enrollment
2015 – Present	Kano State Polytechnic	Lecturer II
2019 – 2021	Department of Civil Engineering, NEU	Assistant
2015 – present	AMEC CAD Training and Management services	Instructor

LANGUAGES

Hausa and English

MEMBERSHIP OF PROFESSIONAL ORGANISATIONS

Member, Nigerian Society of Engineers (NSE), Nigeria

Registered Engineer, Council for the Regulation of Engineering in Nigeria (COREN)

PUBLICATIONS IN INTERNATIONAL REFEREED JOURNALS (IN COVERAGE OF SCI/SCI-EXPANDED):

- **Umar, I. K.,** Nourani, V., & Gökçekuş, H. (2021). A novel multi-model data-driven ensemble approach for the prediction of particulate matter concentration. *Environmental Science and Pollution Research*, 1-15. **(Q2)**
- Nourani, V., Gökçekus, H., **Umar, I. K.,** & Najafi, H. (2020). An emotional artificial neural network for prediction of vehicular traffic noise. *Science of the Total Environment*, 707, 136134. **(Q1)**.
- Nourani, V., Gökçekuş, H., & **Umar, I. K.** (2020). Artificial intelligence-based ensemble model for prediction of vehicular traffic noise. *Environmental Research*, 108852. **(Q1).**
- Nuhu, M., **Umar, I.K.,** Ibrahim, A., Gokcekus, H. (2020). Water quality evaluation of some boreholes and dug-wells in Dorayi. *Desalination and Water Treatment*, 26819, 1–7. **(Q3).**

PUBLICATIONS IN INTERNATIONAL REFEREED JOURNALS (IN COVERAGE OF British Education Index, ESCI, Science Direct, Scopus, IEEE):

- **Umar, I. K.,** & Gokcekus, H. (2019). Modelling severity of road traffic accident in Nigeria using artificial neural network. Jurnal Kejuruteraan, 32(2), 221–227.
- **Umar, I. K.,** & Bashir, S. (2019). Investigation of the factors contributing to truck driver's involvement in an injury accident. Pamukkale University Journal of Engineering Sciences, 26(3), 402–408.

PAPERS PUBLISHED IN OTHER INTERNATIONAL INDEXED JOURNALS

- **Umar, I. K.,** Bashir, S., Alfanda, A. M. U., & Farouk, A. I. B. (2019). Pedestrian's Utilizations of Footbridge in Kano-Nigeria. *ALKÜ Fen Bilimleri Dergisi*, *1*(1), 33-39.

- **Umar, I. K.,** & Bashir, S. (2018). Comprehension of Road Traffic Signs by Various Road Users in Kano City. *Cumhuriyet Science Journal*, *40*(1), 197-203.
- **Umar, I.,** Bashir, S., & Gora, A. (2017). Road traffic accident in kano Nigeria: a case study of kano metropolitan. *Scholars Journal of Engineering and Technology*, *5*(12), 691-697.

PAPERS UNDER REVIEW FOR POSSIBLE PUBLICATIONS

- Nourani, V., Gökçekuş, H., & **Umar, I. K.** Emotional Artificial Neural Network (EANN) a new ANN model in Hydroinformatics
- **Umar, I. K.,** Nourani, V., & Gökçekuş, H. Potential of linear-nonlinear hybrid models for prediction of roadway traffic noise.
- **Umar, I. K.,** Nourani, V., & Gökçekuş, H. An artificial intelligence-based ensemble approach for the prediction of Pm2.5 in cities with high traffic noise.

Book and Book Chapter published

- **Umar, I. K.,** Gökçekus, H., & Ozsahins, D. U. (2021). Comparative Analysis of Flexible Pavement Design Methods Using Fuzzy PROMETHEE. *Application of Multi-Criteria Decision Analysis in Environmental and Civil Engineering*, 173-182.

International Conferences Attended

- **Umar, I. K**., Nourani, V., Gokcekus, H. (2021). Modelling the $PM_{2.5}$ concentration in cities with high traffic noise using artificial intelligence-based ensemble approach. 5th International Conference on "Natural Resources and Sustainable Environmental Management NRSEM-2021". Nicosia, North Cyprus.

- Nourani, V., Gokcekus, H., **Umar, I. K**. (2019). Vehicular traffic noise modelling using adaptive neuro fuzzy inference system. 2nd International Conference on "Environment: survival and sustainability". Nicosia, North Cyprus.

- Gokcekus, H., Nourani, V., **Umar, I. K**. (2019). Application of artificial neural network in modelling vehicular traffic noise. 2nd International Conference on "Environment: survival and sustainability". Nicosia, North Cyprus

- Yahya, M.N., **Umar, I. K.,** Ibrahim, A., & Gokcekus, H. (2019). Water quality evaluation of some boreholes and dug wells in Kano-Nigeria. 2nd International

Conference on “Water Problems in the Mediterranean Countries”. Nicosia, North Cyprus.

- Dayyabu, A., **Umar, I. K.,** & Ozsoy, U. (2017). Severity Assessment of Truck Involved Accident in Northwest Nigeria. 4th International Conference on Transportation in Africa, Abuja.

Conferences Organized

- Member, Organization Committee, 2nd International conference on the environment survival and sustainability, 7 – 11 October 2019. Near East University, Nicosia, Cyprus.
- Member, Organization Committee, 2nd International conference on Water problems in the Mediterranean Countries (WPMC 2019), 06 – 10 May, 2019. Near East University, Nicosia, Cyprus.
- Member, Organization Committee, 2nd International conference on the Cyprus Issue: Past, Present and the Vision for the Future, 1 – 3 April, 2019. Near East University, Nicosia, Cyprus

THESISES

Master

Umar I.K. (2014). *Work Zone Safety Audit and Case Study in Kano*. Unpublished Master thesis, Atilim University, Department of Civil Engineering, Graduate School of Applied Sciences, Ankara, Turkey.

Project

Umar I.K. (2011). *Appraisal of Water Supply System in Bayero University, Kano (New Campus).* Unpublished Undergraduate project (B.SC.), Bayero University Kano, Department of Civil Engineering, Faculty of Engineering, Kano, Nigeria.

COURSES GIVEN (2015-2021)

Undergraduate:

- SUG208 - Engineering Survey
- ICT201 - AutoCAD
- CIV374 - Engineering Hydrology

- CIV371 - Fluid Mechanics
- CIV213 - Strength of Materials
- CIV306 – Computer Application in Civil Engineering
- ECC212 - Dynamics

SPORTS

Badminton, Football

HOBBIES

Reading, movies

YAKIN DOĞU ÜNİVERSİTESİ

Appendix 2

Ethical Approval Letter

Date:22nd January, 2022

To the Graduate School of Applied Sciences

REFERENCE: IBRAHIM KHALIL UMAR (20178443)

The research project titled “**Artificial intelligence-based models for prediction of vehicular traffic noise**” has been evaluated. Since the researcher(s) will not collect primary data from humans, animals, plants or earth, this project does not need to go through the ethics committee.

Title: Dean, Faculty of Civil and Environmental Engineering

Name: Prof. Dr. Huseyin Gokcekus

Role in the Research Project: Supervisor

Title: Professor, Faculty of Civil and Environmental Engineering

Name: Prof. Dr. Vahid Nourani

Role in the Research Project: Co-Supervisor

Appendix 3

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