http://dergipark.org.tr/trkjnat
Trakya University Journal of Natural Sciences, 23(2): 153-165, 2022
ISSN 2528-9691
DOI: 10.23902/trkjnat.1062091

Research Article

MODELLING THE $PM_{2.5}$ CONCENTRATION WITH ARTIFICIAL INTELLIGENCE-BASED ENSEMBLE APPROACH

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Cite this article as:

Umar I.K. & Yahya M.N. 2022. Modelling the $PM_{2.5}$ concentration with artificial intelligence-based ensemble approach. *Trakya Univ J Nat Sci*, 23(2): 153-165, DOI: 10.23902/trkjnat.1062091

Received: 24 January 2022, Accepted: 25 August 2022, Online First: 12 September 2022, Published: 15 October 2022

Edited by:
Güray Doğan

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Key words:
Traffic noise
Sensitivity analysis
Ensemble modelling
Air quality

Abstract: Fine particulate matter ($PM_{2.5}$) has been linked to a number of adverse health effects, hence its prediction for epidemiological studies has become very crucial. In this study, a novel ensemble technique was proposed for the prediction of $PM_{2.5}$ concentration in cities with high traffic noise using traffic noise as an input parameter. Air pollutants concentration (P), meteorological parameters (M) and traffic data (T) simultaneously collected from seven sampling points in North Cyprus were used for conducting the study. The modelling was done in 2 scenarios. In scenario I, $PM_{2.5}$ was modelled using 4 different input combination without traffic noise as input parameter while in scenario II, traffic noise was added as an input variable for 4 input combinations. The models were evaluated using 4 performance criteria including Nash-Sutcliffe Efficiency (NSE), Root Mean Square Error (RMSE), Correlation Coefficient (CC) and Bias (BIAS). Modelling $PM_{2.5}$ with combined relevant input parameters of P, M and T could improve the performance of the model developed with only one set of the parameters by up to 12, 17 and 29% for models containing only P, M and T respectively. All the models in scenario II have demonstrated high prediction accuracy than the corresponding model in scenario I by up to 12% in the verification stage. The Support Vector Regression-based Ensemble model (SVR-E) could improve the performance accuracy of single models by up to 17% in the verification stage.

Özet: İnce partikül madde ($PM_{2.5}$) bir dizi olumsuz sağlık etkisi ile ilişkilendirilmiştir, bu nedenle epidemiyolojik çalışmalar için öngörüsü çok önemli hale gelmiştir. Bu çalışmada, giriş parametresi olarak trafik gürültüsü kullanılarak trafik gürültüsü yüksek şehirlerde $PM_{2.5}$ konsantrasyonunun tahmini için yeni bir topluluk tekniği önerilmiştir. Çalışmanın yürütülmesi için Kuzey Kıbrıs'taki yedi örnekleme noktasından eş zamanlı olarak toplanan hava kirletici konsantrasyonu (P), meteorolojik parametreler (M) ve trafik verileri (T) kullanılmıştır. Modelleme 2 senaryoda yapılmıştır. Senaryo I'de $PM_{2.5}$, trafik gürültüsü olmadan 4 farklı giriş kombinasyonu kullanılarak giriş parametresi olarak modellenirken, senaryo II'de trafik gürültüsü 4 giriş kombinasyonu için giriş değişkeni olarak eklenmiştir. Modeller, Nash-Sutcliffe Verimliliği (NSE), Ortalama Kare Hatası (RMSE), Korelasyon Katsayısı (CC) ve Bias (BIAS) olmak üzere 4 performans kriteri kullanılarak değerlendirildi. $PM_{2.5}$'in ilgili P, M ve T girdi parametreleriyle modellenmesi, yalnızca bir parametre seti ile geliştirilen modelin performansını yalnızca P, M ve T içeren modeller için sırasıyla %12, 17 ve %29'a kadar iyileştirebilir. Senaryo II'deki tüm modeller, doğrulama aşamasında senaryo I'deki karşılık gelen modelden %12'ye kadar yüksek tahmin doğruluğu göstermiştir. Support Vector Regresyon tabanlı Ensemble modeli (SVR-E), doğrulama aşamasında tekli modellerin performans doğruluğunu %17'ye kadar artırabilir.

Introduction

Environmental air and noise pollution induced by vehicular traffic is harmful to human health resulting into many health challenges for urban residents. Incessant exposure to poor air in urban areas has been linked to some life threatening ailments such as lung cancer (Raaschou-nielsen *et al.* 2013), cardiovascular diseases (Newby *et al.* 2015), respiratory diseases (Dong *et al.* 2012) and stroke (Ljungman & Mittleman 2014). Vehicular traffic has been identified as the major source of environmental noise in urban area affecting almost 125 million people (European Environment Agency 2014) and also contributing to more than 64% of particulate matter ($PM_{2.5}$) and nitrogen oxides (NO_x) in the atmosphere (European Environment Agency 2012). Some of the hazardous ambient air pollutants that are related to adverse health effect include $PM_{2.5}$, ozone (O_3), Nitrogen dioxide (NO_2), Carbon monoxide (CO), and Sulphur dioxide (SO_2) (Uzoigwe *et al.* 2013).

The assessment of combined exposure effect to air and noise pollution due to increasing number of world's population in urban areas 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). Recently, the combined exposure effect of air and noise pollution on human health and their spatial relationship have begun to attract 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 particle concentrations and obtained a good result with a determination coefficient of 0.77. Danciulescu & Bucur (2015) found a moderate correlation between the traffic noise and air pollutant concentrations. 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, Ozone and PAH) in urban parks was obtained in a study by Klingberg *et al.* (2017). Gan *et al.* (2012) modelled population exposure to noise and air pollution in large metropolitan Vancouver, Canada using land regression. The results show least correlation ranging from 0.18-0.48 between the traffic noise and the other traffic related pollutants including the NO, NO_2, $PM_{2.5}$ and black carbon. The least correlation of 0.18 was obtained between the traffic noise and aerodynamic $PM_{2.5}$.

The estimation of $PM_{2.5}$ concentration is vital for providing well-timed and complete references for public health risk minimization. It will also help the relevant agencies in providing sustainable countermeasures for future improvements. Several empirical models, one of which is the steady-state Gaussian plume models, for the estimation of various air pollutants at varying times have been developed. Unfortunately, due to large dataset required for the application of these models in addition to vast knowledge of the formation process, the empirical models were not able to provide accurate and reliable results due to the complexity and diversity of the process involved in both transportation and formation of the air (Arhami *et al.* 2013). Motivated with the reliability of machine learning techniques in modelling complex systems by handling multivariate inputs, uncertainty and nonlinearity between the input and the output parameters without requiring prior assumptions, several machine learning techniques were employed for the prediction of air quality parameters. These techniques have demonstrated high prediction accuracy (Cai *et al.* 2009). For instance, Suleiman *et al.* (2016) employed the use of Boosted Regression Trees (BRT) and Artificial Neural Network (ANN) to predict the particle number count (PNC), $PM_{2.5}$ and PM_{10} concentrations in London. The inputs parameters used include NO_2, NO_x, NO, SO_2, CO, NO_{xbg}, NO_{bg}, SO_{2bg}, CO_{bg}, PM_{10bg}, rain, temperature, relative humidity, wind speed, seed of vehicles, and PM_{10dve}. The BRT model performed better than the ANN in terms of both error metrics and goodness of fit measures of the models. 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. Suleiman *et al.* (2019) applied three machine learning approaches in the prediction of $PM_{2.5}$, and PM_{10}, the models provided a good prediction result with about 95% of the predicted values falling within the factor of two of the observed $PM_{2.5}$, and PM_{10} concentrations at the edge of the road. Dunea *et al.* (2015) screened various Feed Forward Neural Network (FFNN) and wavelet-FFNN on the time series data of applied to time series of ground-level PM_{10} and $PM_{2.5}$ fractions, O_3, and NO_2 data recorded in cities of Romania. It was found that both FFNN and the Wavelet-FFNN overestimated $PM_{2.5}$ forecasted values in the last quarter of time series. Although AI models provide good results, the single models sometimes faced with overfitting and overestimation problems.

To overcome some of the drawbacks of the single models as well as eliminating the difficulty in selecting the best model to be used for a particular area, ensemble and hybrid models have gained researchers attention for improved performance accuracy. By using these techniques, the unique features of single models could be captured and also the errors in the individual models could be cancelled out. For example, Sun & Li (2020) developed a stacking driven ensemble technique for forecasting the $PM_{2.5}$ concentration in Beijing-Tianjin-Hebei area using output of the individual models (back propagation neural network, extreme learning machine, Improved back propagation neural network) as inputs parameters for Least squares support vector regression model. The developed stacking-driven ensemble model outperformed all the individual single models with smaller forecasting error and higher generalization capability. Umar *et al.* (2021) also developed a neuro-fuzzy ensemble method for the prediction of $PM_{2.5}$ and PM_{10}. The neuro-fuzzy ensemble model outperformed the single models by 3-20% for PM_{10} and 4-22% for $PM_{2.5}$ subject to the single. Suleiman *et al.*(2016) developed a hybrid model for prediction of $PM_{2.5}$, PM_{10} and PNC, the ANN hybrid models performed better compared to boosted regression tree models and ANN models. In this study, the level of traffic induced $PM_{2.5}$ concentration in North Cyprus was modelled with support vector regression model using the concentration of traffic related air pollutants, traffic data and meteorological data as input variables.

The aim of this study is to determine the interaction between the two urban pollutants (traffic noise and $PM_{2.5}$) and proposed a Support Vector Regression-based Ensemble model (SVR-E) approach for the prediction of $PM_{2.5}$ using traffic noise as input parameter. The aim could be achieved by (i) identifying the relevance of traffic noise in modelling $PM_{2.5}$ (ii) conducting a single and group nonlinear sensitivity analysis between the potential inputs and the $PM_{2.5}$, and lastly (iii) developing an SVR-E model by combining the outputs of three single models (SVR, FFNN, MLR). $PM_{2.5}$ modelled in this study has been an important parameter in defining air quality of an area. The selection of $PM_{2.5}$ for conducting the study was based on its strong adverse effect on human health (Uzoigwe *et al.* 2013). It also acts as the major bench mark for air quality monitoring systems (Van Donkelaar *et al.* 2006).

The proposed methodology for conducting the study involves four main steps (Fig. 1). The first step involves data collection and processing. In the second step, SVR based nonlinear sensitivity analysis was performed to identify the relevance of each parameter as well as that of three categories of input parameters (i.e., pollutants, meteorological and traffic data) in the prediction of the traffic noise. In the third step, $PM_{2.5}$ was modelled using most relevant parameters from all three inputs group combined together for scenario I and II. In scenario I, the traffic noise has not been considered as an input parameter for the $PM_{2.5}$ prediction while all the models developed in scenario II contain traffic noise as one of the input parameters for improved prediction accuracy. The modelling equations were given in Equations 1-8. In step three, the inputs combination that provides highest accuracy was used to develop two additional models (that is FFNN and MLR models). Finally, an SVR-E was used for obtaining the nonlinear average of the outputs obtained from three data driven models (SVR, FFNN, MLR).

Materials and Methods

Scenario I;

$$PM_{2.5} = \left\{ \begin{array}{l} M_1 = f\ (CO2, CO, SO2, PM10) \\ M_2 = f\ (WS, Wdir, Temp, RH) \\ M_3 = f\ (truck, medium\ veh, Bus, cars) \\ M_4 = f\ (\mathrm{CO2, CO, SO2, PM10, WS, Wdir, Temp, RH, truck, medium\ veh, Bus, cars}) \end{array} \right\}$$

Scenario II;

$$PM_{2.5} = \left\{ \begin{array}{l} M_1 = f\ (CO2, CO, SO2, PM10, Leq) \\ M_2 = f\ (WS, Wdir, Temp, RH, Leq) \\ M_3 = f\ (truck, medium\ veh, Bus, cars, Leq) \\ M_4 = f\ (\mathrm{CO2, CO, SO2, PM10, WS, Wdir, Temp, RH, truck, medium\ veh, Bus, cars}, Leq) \end{array} \right\}$$

Data collection

For conducting the study, data from 7 different data collection points in Northern Cyprus (Fig. 2) were collected between 10^{th} - 24^{th} January 2020 from 9am to 7pm. The parameters measured at each of the data collection points include air pollutants concentration (CO_2, CO, NO_2, SO_2, $PM_{2.5}$, PM_{10}), meteorological parameters (atmospheric pressure, relative humidity, temperature, wind direction, and wind speed), traffic data (cars, trucks, buses, and medium vehicles) and equivalent noise level (L_{eq}). The air pollutants and meteorological parameters were measured using the HIM6000 HAZ-SCANNER (HIM6000, USA) having up to 12 sensors. The HAZ-SCANNER was placed on flat surface at 1 m height at each of the data collection points which are located along the roadside. Simultaneously with the air pollutants, 15 minutes equivalent continuous noise level was recorded using a digital Sound Level Meter (SLM) placed at 1.2 m above the ground level and a distance of not more than 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 was measured for 15min. The equivalent sound level in the study area varies from 58 to 80.1 dBA which is higher than the indorsed level of 55 dB set for the European countries (Ilgurel *et al.* 2016). The $PM_{2.5}$ concentration in the study area ranges from 2-106 $\mu g/m^3$ with an average value of 30.28 $\mu g/m^3$ which is high exceeding the optimal guideline value of 15 $\mu g/m^3$ (24-hour mean) recommended by the World Health Organization (Sun & Li 2020). The statistical summary of the data is given in Table 1. The data has a good range which makes it suitable for modelling.

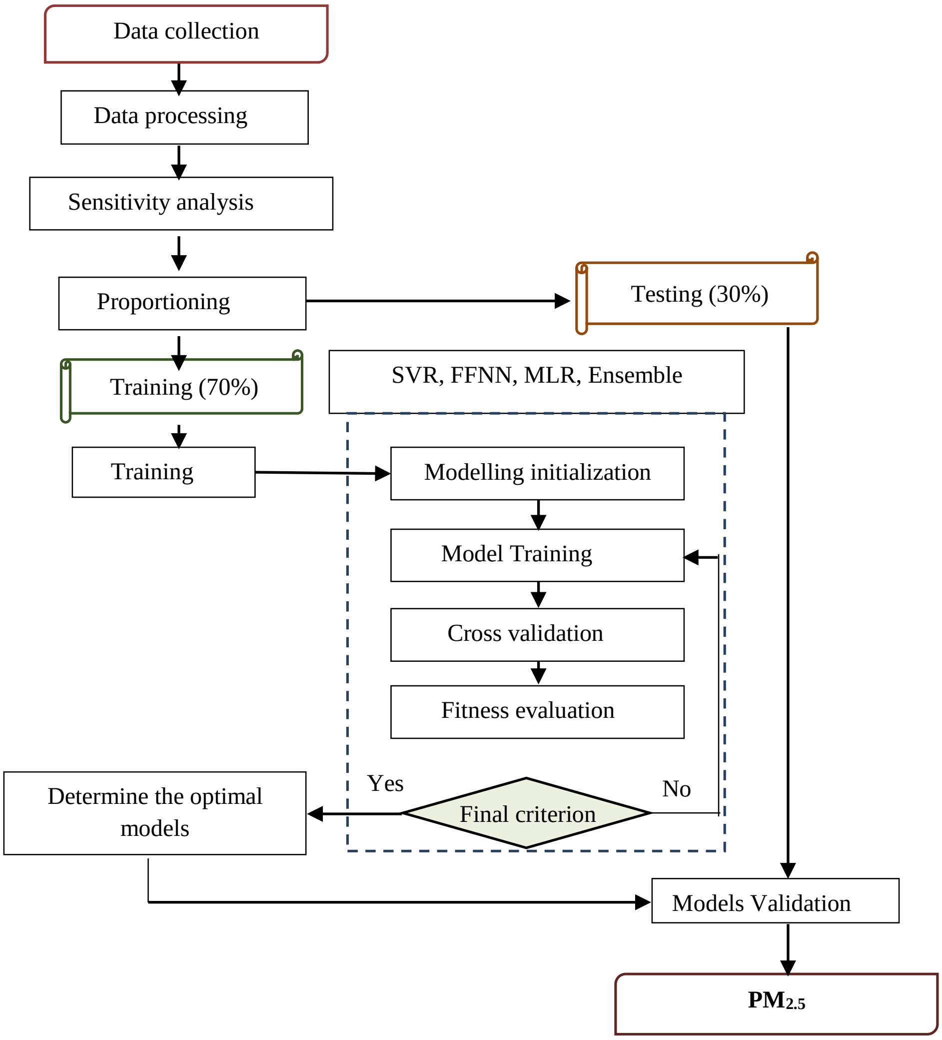

Fig. 1. Schematic diagram of the proposed methodology

Fig. 2. Data collection points

Table 1. Statistical summary of observed data

Parameters	Mean	Standard Deviation	Min.	Max.
RH (%)	41.22	7.87	31.00	60.60
Temp (°C)	15.33	1.17	13.80	17.40
Wdir (deg)	151.47	92.34	36.00	356.40
WS (kph)	2.62	2.05	0.00	6.62
Traffic	121.64	29.54	57.00	191.00
Cars	111.77	29.14	50.00	178.00
Bus	3.27	2.96	0.00	14.00
Medium veh.	4.32	3.26	0.00	21.00
Truck	2.29	1.95	0.00	9.00
P	4.68	2.95	0.00	14.47
CO_2 (ppm)	483.62	9.56	467.40	504.00
CO (ppm)	0.03	0.05	0.00	0.22
NO_2 (ppb)	6.25	6.65	2.00	25.00
SO_2 (ppb)	198.79	130.35	0.00	574.00
PM_{10} ($\mu g/m^3$)	79.61	70.10	4.00	255.00
Noise	70.28	4.53	58.70	80.10
$PM_{2.5}$($\mu g/m^3$)	30.28	23.03	2.00	106.00

Relative humidity (RH), Temperature (Temp), Wind direction (Wdir), Wind speed (WS), Traffic volume (Traffic), Volume of cars (cars), Volume of Buses (Bus), Volume of medium vehicles (medium veh), volume of trucks (truck), Percentage of heavy vehicles (P), Carbon dioxide (CO_2), Carbon monoxide (CO), Nitrogen oxide (NO_2), Sulphur (IV) oxide (SO_2), Particulate matter 10 (PM_{10}), Equivalent noise level (Leq)

Sensitivity analysis

Sensitivity analysis has been used as one of the most important tools for removing less important and irrelevant input parameters in modelling. Excluding the irrelevant input parameters in modelling is very essential as it reduces the model's complexity and computation time (Nourani *et al.* 2020b). In this study, two forms of SVR-based nonlinear sensitivity analysis were used. The first is the single-input single-output sensitivity analysis. Here each parameter is used to model $PM_{2.5}$ using the SVR model and the corresponding Nash-Sutcliffe Efficiency (NSE) value is recorded, the parameter that gives highest NSE value with $PM_{2.5}$ is considered to be the most relevant and vice-versa. In the second form of the sensitivity analysis which is the group sensitivity analysis, all factors in a particular group (traffic) are used to model the $PM_{2.5}$ and the corresponding NSE value is computed, the group of data that gives higher NSE value is considered as a dominant group for the prediction of $PM_{2.5}$.

Machine learning methods

Feed Forward Neural Network (FFNN)

FFNN is one the most widely used ANN models used for bagging the complex and the nonlinearity relationship between the independent and dependent parameters (Jahani & Mohammadi 2019). In FFNN, information is transmitted and flows only in the in forward direction (Ghaffari *et al.* 2006). The FFNN is generally accepted owing to its simplicity in capturing and modelling complex and nonlinear pattern in problems (Rumelhart *et al.* 1986). The appropriateness of the model to establish a pattern in the data by learning from experience and capture the interaction between the inputs and the target parameter without the need to identify the physical connection between the variables makes it suitable and essential in modelling complex engineering problems (Kumar *et al.* 2014). The collaborative link amongst neurons in the FFNN is utilized to process the info and create a relationship rather than creating any multifaceted mathematical model. Generally, backpropagation algorithms are used in training FFNN. To train the FFNN model, several adjustable weights are primed and multiplied by the inputs, the cumulative sum then goes through an activation function which handle the nonlinearity of the data before yielding out the output result (Ghaffari *et al.* 2006). The optimum number of hidden neurons is chosen by trial-and-error method. The structure that gives lowest root mean square error between the observed and the predicted data is considered to be the optimum.

Support vector regression (SVR)

SVM was developed using statistical learning theory. The fundamental principle of the SVM execution in pattern recognition is the linear or non-linear mapping of the input vectors into a potentially higher dimension of feature space. The type of kernel function determines the mapping process. Then, an optimal hyperplane was built to achieve a maximum separation of two classes. In other words, SVM training was developed to address the issue of over-fitting and it excels at processing a large number of features. The readers can refer to Wang *et al.* (2015) and Nourani *et al.* (2020b) for more details about SVR modelling. The SVR equation can be expressed as (Wang *et al.* 2015):

$$y = f(x) = \omega\varphi(x_i) + b \tag{1}$$

where ω denotes the m-dimensional weight vector, $\varphi(x_i)$ signifies feature spaces, x stands for the non-linearity mapped from input vector and b represent the bias (Wang *et al.* 2015).

Multi linear regression

Linear regression analysis is a common technique used by scientist to simulate and analyze dependency between distinct parameters. Regression analysis benefits to cognize how a certain value of the regressor parameter deviates when any one of the predictors changed, when the other predictors were kept unchanged. It also help in exploring the direct interactions describing the relationship between the parameters (Doğan & Akgüngör 2013). The predictors and regressor parameters are related by (Elkiran *et al.* 2018):

$$y = b_0 + b_1x_1 + b_2x_2 + b_3x_3 + \cdots + b_ix_i + \xi \tag{2}$$

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.

Ensemble technique

Ensemble technique as post-processing technique has demonstrated ability in improving model's prediction by combining outputs of several models. It was found to be less risky to use a combination of relatively simple models than to use a single complex and expensive model (Winkler and Makridakis 1983). In this paper, SVR based ensemble and Simple Average Ensemble (SA-E) techniques were developed using the output of the single models.

In the SA-E, the mean of the outputs ($PM_{2.5}$ concentration) of the SVR, FFNN and MLR models is considered as the predicted $PM_{2.5}$ concentration and given as:

$$\overline{PM} = \frac{1}{N}\sum_{i=1}^{n_m} PM_i \quad (3)$$

in which $\overline{PM}$ shows the result of simple average ensemble method ($PM_{2.5}$ concentration), n_m is the number of single models used (in this study, n_m =3) and N_i stands for the outcome of the i^{th} method (i.e., SVR, FFNN and MLR).

Data preprocessing and performance evaluation

Data preparation such as normalization, standardization etc. is required prior to the development of data driven models for obtaining accurate results. Normalization was performed on all the data including the inputs and the target parameters to bring all data into same range between unity and zero (0 and 1). This helps prevent that data with higher numeric values to dominate over those with lower values and to also remove the dimensions of the data. Normalization also improves the model's accuracy by reducing the complexity, computational requirement, redundancy in the data and also time required to attain the global minima (Nourani *et al.* 2020a). The data was normalized using:

$$N_{norm} = \frac{N - N_{min}}{N_{max} - N_{min}} \quad (4)$$

where N_{norm} is the normalized value, N, N_{max} and N_{min} are the observed, maximum and minimum values, respectively.

The efficiency of the models was evaluated using NSE, Root Mean Square Error (RMSE), Coefficient of Correlation (CC) and BIAS. The NSE values ranges from -∞ to 1 and it is a parameter that indicates how well the model fits the observed values. A perfect model has an NSE value of 1 and the model efficiency decreases as the value moves far from 1 and vice versa. RMSE as one of the best measures for computing the model's performance is 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 & Sayyah 2012). The CC ranges from -1 to 1, the correlation increases as the values moves away from 0. The strength of the correlation is not dependent on the direction or sign. A positive value shows direct proportionality between the parameters while a negative correlation shows an inverse proportionality. For BIAS, the closer it approaches, the better the model. The performance evaluations mentioned can be computed using Equations 5 - 8, respectively.

$$NSE = 1 - \frac{\sum_{i=1}^{n}\left(N_{obs_i} - N_{pre_i}\right)^2}{\sum_{i=1}^{n}\left(N_{obs_i} - \overline{N_{obs_i}}\right)^2} \quad (5)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(N_{obs_i} - N_{pre_i}\right)^2}{n}} \quad (6)$$

$$CC = \frac{\sum_{i=1}^{n}\left(N_{obs_i} - \overline{N_{obs_i}}\right)\left(N_{pre_i} - \overline{N_{pre_i}}\right)}{\sqrt{\sum_{i=1}^{n}\left(N_{obs_i} - N_{obs_i}\right)^2 \sum_{i=1}^{n}\left(N_{pre_i} - N_{pre_i}\right)^2}} \quad (7)$$

$$BIAS = \sqrt{\frac{\sum_{i=1}^{n}\left(N_{obs_i} - N_{pre_i}\right)^2}{n}} \quad ..(8)$$

where, n is the number of observations, $\overline{N}_{obs}$ is the mean observed value, N_{obs} is the observed value, and N_{pre} is the predicted value.

Results

Sensitivity analysis result

The use of the relevant input parameter in any data driven model is essential for obtaining efficient and accurate result. This is because inclusion of nonrelevant parameters will increase the computational requirement of the model and in some cases reduced the performance of the models (Nourani & Sharghi 2020). In the first stage of the study, a single-input single-output sensitivity analysis was conducted using the SVR model. The result of the single-input single-output is given in Table 2. It can be seen from the result that *Wdir*, NO_2, PM_{10}, *RH%*, *Leq*, *Temp* have highest relevance for the $PM_{2.5}$ prediction with an NSE of at least 40%. The high relevance of three parameters in the meteorological parameters group indicates that, the distribution of the $PM_{2.5}$ is significantly influenced by *Temp*, *RH%* and *Wdir*. The result was supported by a study reported by Whalley and Zandi (2016) where meteorological parameters such as temperature, wind speed and direction, relative humidity and solar radiation were identified among the major factors affecting particulate matter concentration. For example, cold temperatures increase the chances of inversion layer formation which prevents the upward movement of air from the layers below it hence traps the particulate matter near the ground and results in higher particulate matter concentration. An inverse correlation was also found between particulate matter and humidity when rainfall is intense at high relative humidity. The result of the sensitivity analysis is in line with findings obtained in other parts of the world. High correlation and dependency between the meteorological parameters has been established by several studies (Lou *et al.* 2017, Wang & Ogawa 2015, Wang *et al.* 2019). The high correlation between the $PM_{2.5}$ and the NO_2 has also been obtained by other studies such as the study of Yangyang *et al.* (2015) in determining the correlation between spatial distribution of $PM_{2.5}$ and other air pollutants in 31 Chinese provincial capital cities. The t-test performed between the observed and the predicted $PM_{2.5}$ obtained from the single-input single-output sensitivity analysis shows that all the parameters are significant with the exception of the WS and CO which are found to be statistically insignificant.

Table 2. Single-input single-output sensitivity analysis result.

Group	Parameters	NSE
Meteorological	*RH (%)*	0.45
	Temp (°C)	0.40
	Wdir (deg)	0.52
	WS (kph)	0.06
Traffic	*Traffic*	0.19
	Cars	0.25
	Bus	0.12
	Medium veh	0.13
	Truck	0.35
	P	0.22
Air pollutants	CO_2 *(ppm)*	0.10
	CO (ppm)	0.05
	NO_2 *(ppb)*	0.49
	SO_2 *(ppb)*	0.17
	PM_{10} *(µg/m³)*	0.47
Traffic noise	*Leq*	0.44

Relative humidity (RH), Temperature (Temp), Wind direction (Wdir), Wind speed (WS), Traffic volume (Traffic), Volume of cars (cars), Volume of Buses (Bus), Volume of medium vehicles (medium veh), volume of trucks (truck), Percentage of heavy vehicles (P), Carbon dioxide (CO_2), Carbon monoxide (CO), Nitrogen oxide (NO_2), Sulphur (IV) oxide (SO_2), Particulate matter 10 (PM_{10}), Equivalent noise level (Leq)

Followed by the single-input single-output sensitivity analysis, the group sensitivity analysis 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 & 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. The results of the group sensitivity analysis for scenario 1 were presented in Table 3. 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 BIAS value of 0.4218 in the verification stage. The meteorological parameters modelled $PM_{2.5}$ 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. The data is more compressed along the diagonal bisector lines of the charts (Fig.3) for M4 signifying better goodness of fit when all the parameters were used to predict the concentration of $PM_{2.5}$ in the atmosphere.

In scenario II, four models (M5-8) were also developed to model the $PM_{2.5}$ and the result was presented in Table 4. It can be seen that M5 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 (M6) and traffic data (M7) as inputs with NSE and RMSE values of 0.7399 and 0.0810, respectively in the verification stage. The M8 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 M8 model has improved the performance of M5, M6 and M7 models by 12%, 16% and 19%, respectively in the verification stage. The models' goodness fit in the verification stages were presented in Fig. 4. It can be clearly observed that the data is compressed more along the diagonal bisector line for the M8 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 $PM_{2.5}$ in models M5, M6, M7 and M8 could improve 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 3. Results of the $PM_{2.5}$ concentration model using different input groups without traffic noise (scenario I)

MODELS	Inputs	Training				Verification			
		NSE	RMSE	CC	BIAS	NSE	RMSE	CC	BIAS
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

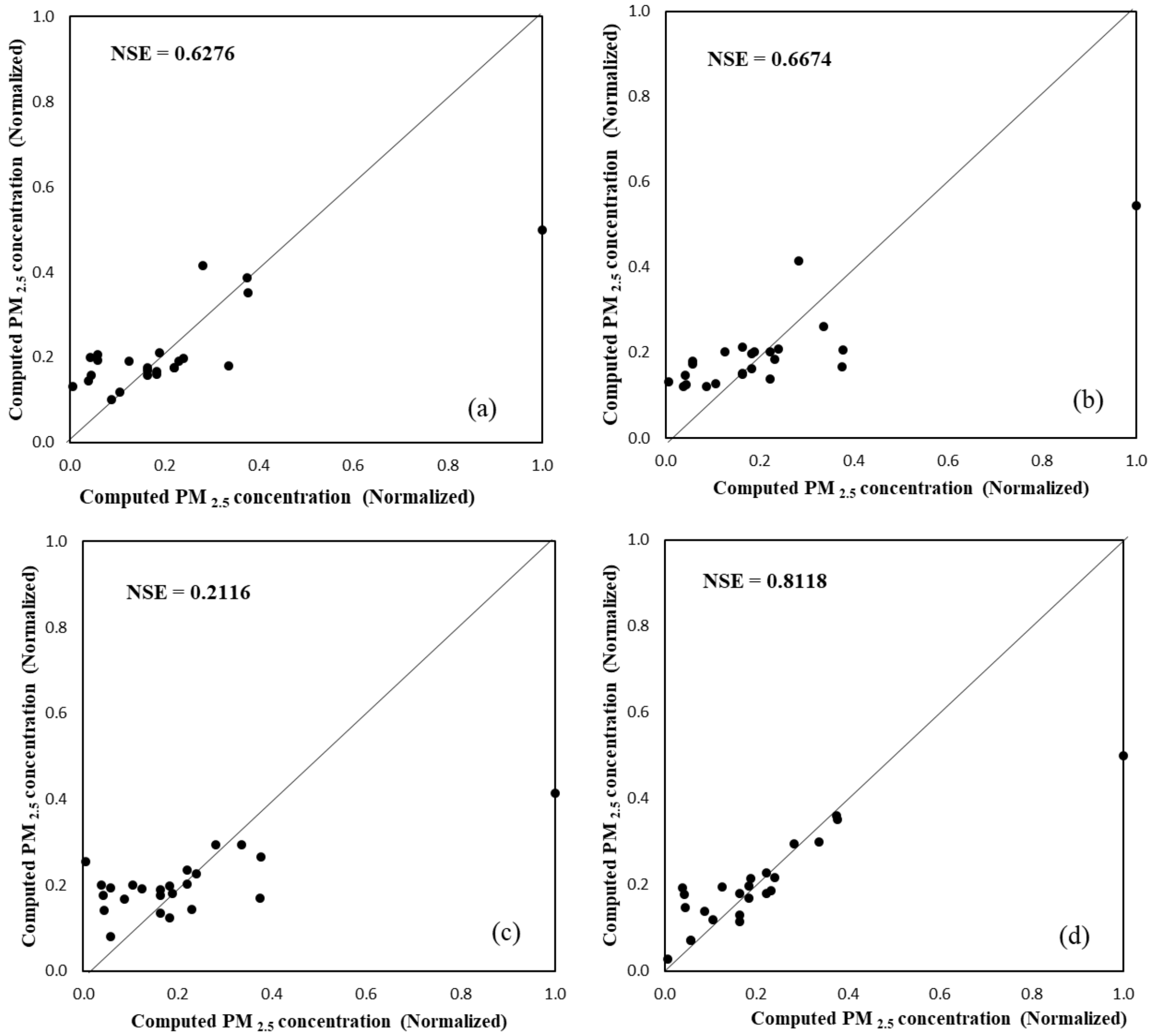

Fig. 3. Scatter plots between computed and observed data in the verification stage for a) M1, b) M2 and c) M3 d) M4.

Table 4. Results of $PM_{2.5}$ concentration model using different input groups with traffic noise (scenario II)

MODELS	Inputs	Training				Verification			
		NSE	RMSE	CC	BIAS	NSE	RMSE	CC	BIAS
M5	P, L_{eq}	0.7969	0.1178	0.8742	0.2271	0.7399	0.0810	0.6779	0.3680
M6	M, L_{eq}	0.7438	0.1305	0.8592	0.2620	0.6930	0.0873	0.6168	0.4217
M7	T, L_{eq}	0.6390	0.1525	0.7739	0.2757	0.5770	0.1012	0.3577	0.4671
M8	P, M, T, L_{eq}	0.8827	0.0577	0.9207	0.2572	0.8642	0.0993	0.8536	0.1509

Taylor diagram was used to compare the performances of all the models in scenarios I and II (see Fig. 5). Taylor diagram contrasts three statistical measure [standard deviation, RMSE and correlation (CC)] graphically. Therefore, it gives clear and a reliable evaluation of the relative performance and efficiency of four different machine learning models. In the Taylor diagram, the radial distance from the origin is directly proportional to the standard deviation of the data, the azimuthal position of the test field gives the correlation between the measured and observed $PM_{2.5}$ while the centered RMSE value is related to the distance between the observed and the predicted $PM_{2.5}$ with the same units as the standard deviation (Taylor 2001). The RMSE value is inversely related to the correlation, hence the RMSE increases with decrease in correlation between the observed and the predicted $PM_{2.5}$. A perfect model is set apart by the reference point with the CC equivalent to 1 (Yaseen *et al.* 2018). In the Taylor diagram, it can be seen that M8 outperformed all the models with highest CC value and lowest RMSE value, the standard deviation is also less than that of the actual data indicating that the good result obtained in M8 does not have high risk of overestimation.

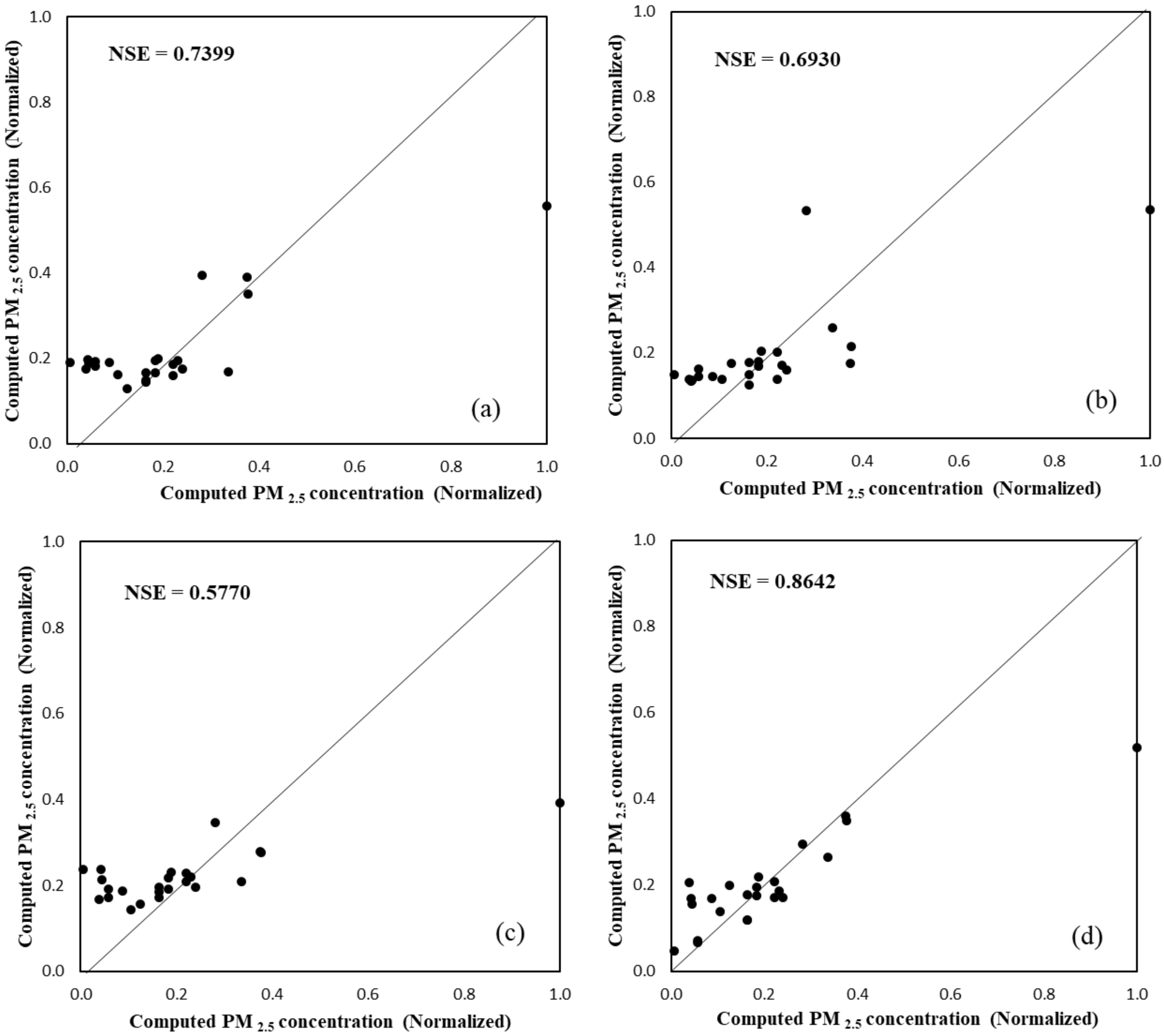

Fig. 4. Scatter plots between observed and computed and $PM_{2.5}$ concentration in the verification stage for a) M5, b) M6 and c) M7 d) M8.

<u>*Single models result*</u>

Furthermore, for comparing the performance of the SVR in 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 5. 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 $PM_{2.5}$ in the study area than the other data driven models used. The MLR gives the least NSE value since it only captures the linear pattern in leaving the nonlinear relationship uncaptured. Radar plot (Fig. 6) was also used for graphical comparison of the models in training and verification stage and better performance was seen in the SVR model. A high stability was also observed by the models where a small difference was obtained between the NSE values in training and verification stage of the models.

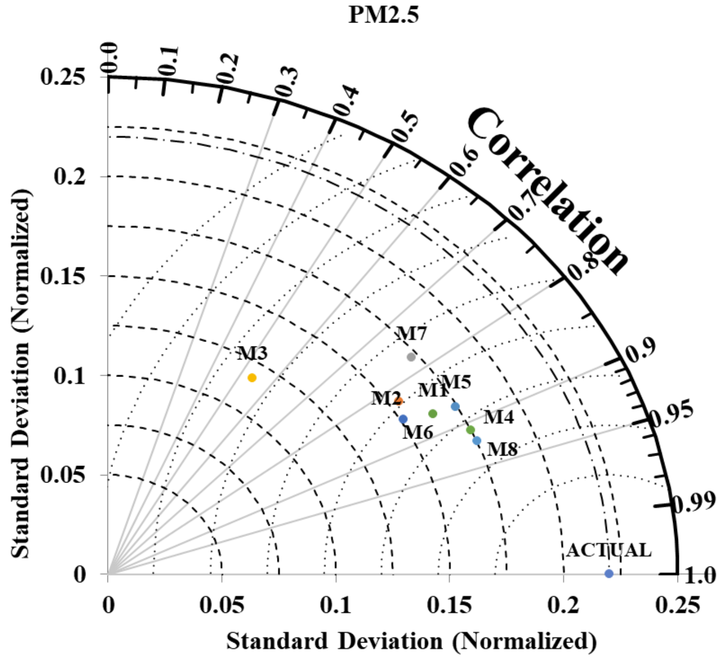

Fig. 5. Taylor diagram comparing the performance of the developed models

Table 5. Comparison between SVR, FFNN and MLR modelling results for $PM_{2.5}$ prediction

MODELS	Inputs	Training				Verification			
		NSE	RMSE	CC	BIAS	NSE	RMSE	CC	BIAS
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

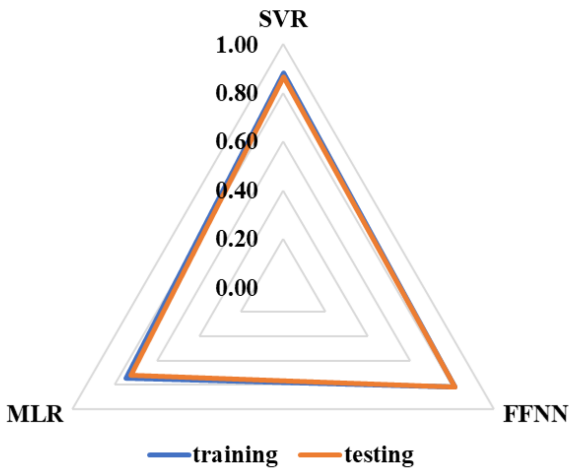

Fig. 6. Radar plots comparing the NSE values for SVR, FFNN and MLR in $PM_{2.5}$ prediction in testing and verification stage

Ensemble models result

In the last stage of the modelling, an ensemble approach was used by combining the outputs of 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 results (Table 6) show higher performance of the nonlinear ensemble techniques over the linear ensemble models and are supported by Nourani *et al.* (2020a) where they mentioned that, nonlinear averaging or ensembles provides better results than the linear averaging techniques. The results show that the SVR-E improved the prediction accuracy in both training and verification stage. The SVR-E outperformed the SA-E by 11% in the training stage and 7% in the verification stage. Also, in terms of RMSE, R and BIAS, SVR-E performed better than the SA-E. 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.

Table 6. Ensemble modelling results.

MODELS	Training				Verification			
	NSE	RMSE	CC	**BIAS**	**NSE**	**RMSE**	**CC**	**BIAS**
SVR-E	0.9535	0.0526	0.9756	0.0836	0.8914	0.0539	0.8682	0.2240
SA-E	0.8440	0.0963	0.9217	0.1000	0.8273	0.0624	0.8060	0.3000

Table 7. t-Test: Paired Two Sample for Means

	Observed	**M1**	**M2**	**M3**	**M4**	**M5**	**M6**	**M7**	**M8**
Mean	0.2719	0.2719	0.2722	0.2693	0.2639	0.2705	0.2760	0.2332	0.2644
Variance	0.0490	0.0490	0.0232	0.0300	0.0312	0.0272	0.0241	0.0139	0.0310
Pearson Correlation		0.8751	0.8577	0.7749	0.9241	0.8713	0.8271	0.5389	0.9107
t Stat		-0.0585	0.0249	-0.1589	-0.7699	-0.1038	0.2727	-1.7719	-0.6701
P(T<=t) one-tail		0.4767	0.4901	0.4371	0.2219	0.4588	0.3929	0.0403	0.2525
t Critical one-tail		1.6663	1.6663	1.6663	1.6663	1.6663	1.6663	1.6663	1.6663
P(T<=t) two-tail		0.9535	0.9801	0.8742	0.4438	0.9176	0.7858	0.0806	0.5049
t Critical two-tail		1.9935	1.9935	1.9935	1.9935	1.9935	1.9935	1.9935	1.9935

A t-test was performed, on the best performing model, with the null hypothesis that the sample means of the observed and the predicted $PM_{2.5}$ values for the testing dataset are not different. The value of t-stat was calculated and compared with t-critical (Table 7). The value of t-stat is less than t-critical (at a 5% significance level), indicating that the alternative hypothesis can be rejected and null hypothesis retained. These results show that the values of $PM_{2.5}$ predicted using the proposed models fit well with the observed data.

Conclusions

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 exceeds the recommended noise level of 55dBA for European countries. Also, the average $PM_{2.5}$ concentration in the area is higher than the optimal level of 15 $\mu g/m^3$ (24-hour mean) recommended by World Health Organization (WHO). The modelling results show 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. The models combining all the parameters from the three inputs class (P, M and T) as input parameters provide higher prediction accuracy than the models with input from one category of the input parameters and could provide an improved performance of up to 12, 17 and 29% for models containing only P, M and T-category, respectively. 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. 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 in future studies.

Ethics Committee Approval: Since the article does not contain any studies with human or animal subject, its approval to the ethics committee was not required.

Author Contributions: Concept: I.K.U., Desing: I.K.U., Execution: I.K.U., Material supplying: I.K.U., Data acquisition: M.N.Y., I.K.U., Data analysis/interpretation: I.K.U., M.N.Y., Writing: I.K.U., M.N.Y., Critical review: I.K.U., M.N.Y.

Conflict of Interest: The authors have no conflicts of interest to declare.

Funding: The authors declared that this study has received no financial support.

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