

Application of Artificial Neural Network to Predict Exhaust Emissions from Road Transport

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The research is supported by BASARSOFT information technology Inc. company (Sponsoring information)

Abstract

Vehicle manufacturers have to meet the standards due to the emission standard limitations. For this reason, every new vehicle must satisfy the limits of emission regulations by passing the driving cycle test accepted by their markets. However, even the new cars satisfy emission limits, our environment is being polluted more than expectations due to the old vehicles used in transportations and unrepresentative driving cycle for real world conditions so that real time exhaust emissions were analyzed in this study. It is aimed to calculate the exhaust gas released by road transports by using IPCC second approach method in Istanbul. Then an artificial neural network model was developed to predict a correlation between real-time exhaust emissions and vehicle number, mean speed. With using different training functions, it is demanded to define the optimum percentage error between the target and the predicted values. It was observed that the ANN model can predict exhaust gases with correlation coefficient in the range of 0.97–0.99. This study shows that the created ANN can be used to accurately predict the greenhouse gas in Istanbul.

Keywords: Artificial neural network, greenhouse gas, IPCC second approach.

1. Introduction

The emissions released from road transport are the one of the main source of air pollution. According to a review of the CLRTAP data by European Environment Agency, road transport is the most significant source of NOx, CO, HC (without Methane) and PM emissions [1]. So there is some limitation set by European Commission (EC) to restrict the released pollutant as CO, hydrocarbons and NOx as well as greenhouses gases [2]. However, certification driving cycles as NEDC or FTP-75 does not represent the real world conditions despite new developments [3,4]. Because of this unrepresentative situation, research on Real-World driving and total emissions of vehicle fleets have become popular topic for automotive engineers. To get the real world emissions portable emissions measurement systems (PEMs) and to calculate total pollutants from road transport some tools as COPERT, MOVES, MOBILE, HBEFA, ARTEMIS, VERSIT, GLOBEMI and EMV were used [5-9].

In the present study, by using IPCC second approach methodology, total exhaust emissions were calculated and then with created Artificial Neural Network (ANN) model, road transport emissions were predicted. In the literatures, it was shown that the use of ANN is a powerful and useful modelling tool that has the ability to identify complex relationships from input–output data [10]. Measuring the exhaust emissions released by road transports cases are time consuming and expensive. Alternatively, the performance and exhaust emissions of vehicles depending on vehicle number and mean speed of vehicles can be modelled using ANNs, which allow the modelling of complex physical phenomena without requiring explicit mathematical representations.
The created new ANN modelling can be applied to predict the output parameters of the system as long as enough experimental data for training, validating and testing are provided. In this study, it is aimed to calculate CO, HC, NO, PM emissions released from road transportation in İstanbul between October and December on Mondays in 2017 by MATLAB software.

2. Methodology

2.1 IPCC Second Approach Methods

To road transport emission calculation, there are three common used ways which are IPCC approaches. While the first approach of IPCC (Tier I) uses the total fuel consumptions, total vehicle number and total mileage of each vehicle, second approach of IPCC (Tier II) uses vehicle types, emission standards and engine sizes additionally. The third IPCC approach is extended model of Tier II and it uses speed dependent emission factors [11].
In this study, with using IPCC second approach, total road transport emissions such as CO, HC (without CH4), NOx, PM and CO2 are calculated for İstanbul between October and December on Mondays in 2017. The Tier II method is given in Equation 1.

$$E_{i,j} = \sum_k (N_{j,k} * M_{j,k} * EF_{i,j,k}) \qquad (1)$$

$EF_{i,j,k}$ is emission factor and i represents pollutant type, j represents vehicle categories and k represent vehicle technologies such as emission standards or engine size. $M_{j,k}$ and $N_{j,k}$ represent road mileage and vehicle number of cars which have j categories and k technologies respectively. The emission factors which will used in this equation are taken from EMEP/EEA air pollution guide [12].

2.2 Artificial Neural Network Model

Artificial neural networks are computing systems composed of neurons are used to solve complex and nonlinear functions, which attempt to simulate the structure and function of biological neurons [13]. Nonlinear basic model of neural computation is shown in Fig. 1. A neural network system has three layers; input layer, hidden layer and output layer. In this study, among the various kinds of ANN approaches, the back propagation (BP) learning algorithm, which has become the most popular in engineering utilization was used. The created network has one input layer, one hidden layer and one output layer. To train and test the neural networks, input data depending on targets were required .[14]. In developing the ANN model, the available data set was divided into two section, one to be used for training of the network (70% of the data), the remaining was used to verify the generalization capability of the network.

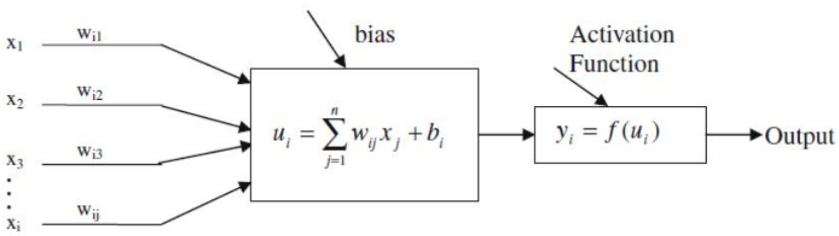

Figure 1. Nonlinear model of neural computation [10]

The inputs are multiplied by the corresponding weight of the neuron connection. A bias b_i can be defined as a type of connection weight with a constant nonzero value added to the summation of inputs and corresponding weights u given as follows:

$$u_i = \sum_{j=1}^{n} w_{ij} + b_i \quad (2)$$

$$y_i = f(u_i) \quad (3)$$

The summation u_i is transferred using a scalar to scalar function called an activation or transfer function $f(u_i)$ to yield a value called the unit's activation given as neural system [10]. The predictive ability of ANNs results from training in experimental data and subsequent validation with independent data [15]. The basic element of an artificial neuron is shown in Fig 2. The artificial neuron is mainly composed of weight bias and activation function. Each neuron receives $x_1, x_2, \dots, x_n$ inputs added to a weight x_i that indicates the link strength of a particular input for each connection.

Levenberg Marquardt algorithm and scaled conjugate gradient algorithm which are the most widely used training algorithm for the multi-layer neural network is a gradient descent technique to minimize the error for training. In this study, ANNs output are compared training with Levenber Marquardt and conjugate gradient algorithm. It has been decided which algorithm works better in ANN.

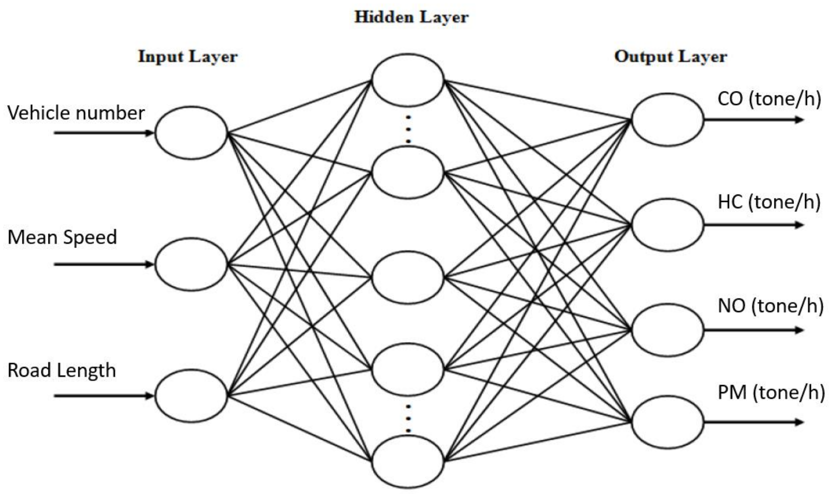

Figure 2. The structure of the artificial neural network.

In this study, experimental results obtained from the measuring are used as the training and test data for the ANN model. The architecture of the ANN for the predicting exhaust emission is shown in Fig. 2. The inputs of the ANN model are vehicle number, mean speed and road length. The outputs are the CO, HC, NO, PM emissions. According to results given by the neural network, the coefficient of correlation (R) between the target and the output values. It is defining as follows [14]:

$$R = \frac{\overline{t.o} - \bar{t}.\bar{o}}{\sqrt{[\overline{t^2} - (\bar{t})^2] - [\overline{o^2} - (\bar{o})^2]}} \quad (4)$$

where t is the target value, o is the output value.

3. Vehicle Activity Data

The number of vehicles, average speed and the road lengths were taken from BASARSOFT company for all road type in Istanbul. The data collected from road were divided into half-hour time periods and sections. The sections are chosen with respect to road type, link road and traffic rules such as traffic lamps, signpost or crosswalk etc. An example of road sections is given in Fig. 3.

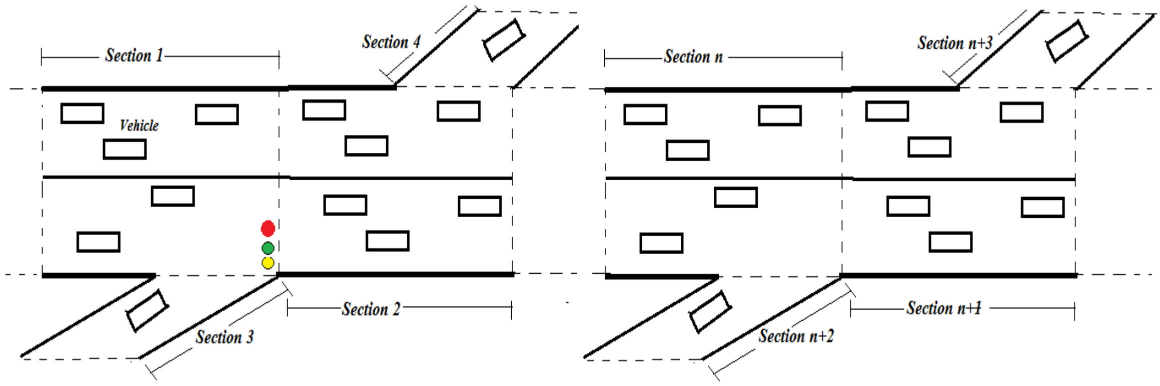

Figure 3. BASARSOFT road section method example.

To determine the total exhaust emissions, with using datum obtained from BASARSOFT, some assumptions about vehicle categorize, fuel type, engine size and emission standard were considered. The number of vehicle classes with these assumptions is calculated from TURKSTAT datum. All vehicles categorized in five main part as passenger car, Light-Duty, Heavy-Duty, bus and motorcycle. After this classification all categories divided into the fuel section like as gasoline fueled, diesel fueled and LPG fueled cars. While doing these sorting about fuel types, some assumptions, as there is no LPG fueled car except for passenger car, 1.5 percent of Light-Duty vehicles are gasoline fueled, all buses are diesel fueled (CNG fueled buses are ignored) and all motorcycles have gasoline engine, are used to determine the number of vehicle in different groups. On the other hand, the passenger car group divided into the four subgroup by means of engine size. By using TURKSTAT statistical data about road transportation for Turkey, we calculated the percentage of vehicle technologies in different groups and then we applied them to all road type in İstanbul [16-19].

On the other hand, based on the date of emission regulations in Turkey, vehicle numbers of different emission groups are calculated with using TURKSTAT data about vehicle age [20]. The starting date of EURO emissions regulation in Turkey is given in Table 1 [21].

As seen in Table 1, the date of enter into force of emission standards in Turkey is not synchronized with European. Starting from 1994, by providing convenience to manufactures in Turkey, soft transition of emission regulation was implemented [21]. In 2002, to catch European country, EURO III regulation was forced to provide for new vehicle without enforcing EURO II. On the other hand, due to the bad quality fuel of diesel cars, EURO I regulation was implemented after 2002. Also for this study, it is assumed that same emission regulation as diesel vehicle is applied to LPG cars, since there is not enough information about LPG emission standards.

Table 1. The date of enter into force of emission regulations in Turkey.

DATE	EMISSION REGULATION		
	GASOLINE	DIESEL	LPG
2015 and after	EURO VI	EURO VI	EURO VI
2010-2014	EURO V	EURO V	EURO V
2006-2009	EURO IV	EURO IV	EURO IV
2002-2005	EURO III	EURO I	EURO I
2001	32 % EURO I + 68 % 15.04	WER	WER
2000	30 % EURO I + 70 % 15.04	WER	WER
1999	21 % EURO I + 79 % 15.04	WER	WER
1998	15 % EURO I + 85 % 15.04	WER	WER
1997	9,4 % EURO I + 90,6 % 15.04	WER	WER
1996	4 % EURO I + 96 % 15.04	WER	WER
1995	1,8 % EURO I + 98,2 % 15.04	WER	WER
1994	1 % EURO I + 99 % 15.04	WER	WER
1993 and before	WER	WER	WER

4. Results and Discussion

With using BASARSOFT data and TURKSTAT data, number of each vehicle categories found and with applying emission factor for each vehicle segment and emission standard, we get total emissions released from road transport. For accurate comparison of emissions from different vehicle class, we must consider vehicle number for each category, energy consumptions and mileage of each vehicle in per time periods. Due to the insufficient information, it is assumed that ratio of each vehicle class in İstanbul represented in all road types. As a results, according to BASARSOFT data, total vehicle numbers in per time period and mean vehicle speed in last three months in 2017 are given in Fig. 4.

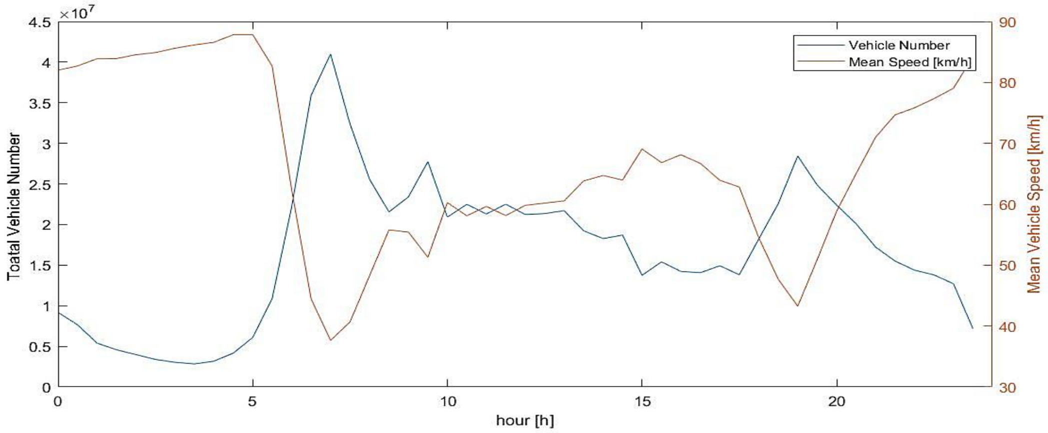

Figure 4. Total vehicle number and mean vehicle speed in Monday.

In this study, exhaust emissions released from passenger cars are investigated in detail. Because passenger car corresponds to 66,6 % of total vehicle in İstanbul and approximately 45 percent of them is LPG, 36,5 percent of them is diesel and 18,5 percent of them is gasoline fueled vehicle.

At Fig.5a, total CO emission released from passenger cars are showed. 70,6 percent of total amount of CO emission is released from passenger car and 57 % of them is from LPG, 39 % of them is from gasoline and the rest of them is from diesel vehicles. Due to the lean combustion in diesel engine, CO emissions is so low. But gasoline and LPG fueled engines are the major source of CO emissions because of stoichiometric or rich combustion. In fact, with converting vehicle from gasoline to LPG, we can able to reduce CO emissions due to the lower H/C ratio [22,23]. But CO emissions caused by LPG vehicle are more than gasoline vehicle's, since the amount of LPG vehicle is approximately 2,4 times of gasoline ones.

At Fig. 5b, HC (without CH_4) emission released from passenger cars are given. 39 percent of total amount of Non-Methane volatile organic compounds (NMVOC or HC) emission is released from passenger car and 68 % of them is from LPG, 26 % of them is from gasoline and the rest of them is from diesel vehicles. The main source of HC emissions (52 % of total) is motorcycle because it is approximately 7,7 percent of total vehicle and the assumption that it is all two stroke engine. As expected, the lowest HC emitted from diesel cars. However, HC caused from LPG vehicle is the main part of total HC gases due to the large amount of vehicle fleet and the assumption that generally the old gasoline vehicles converted to LPG.

At Fig. 6a and 4b, total NO and PM emissions released by passenger car is given. 44,7 percent of total amount of NO emission is caused by passenger car and 50 % of them is from LPG, 37 % of them is from diesel and the rest of them is from gasoline vehicles. Due to the enough oxygen and high cylinder temperature leaded by high compression ratio of diesel engine, the diesel vehicles are the main source of NO emissions. But half of the NO emissions of passenger cars is caused by LPG vehicles, since number of LPG car is the highest and approximately 38,8 percent of LPG cars are in pre-Euro class and have not catalytic convertors or EGR systems. At Fig. 6b, PM emissions of passenger cars is given. 39 percent of total amount of PM emission is caused by passenger car and 97 % of them is from diesel, 2 % of them is from LPG and 1 % of them is from gasoline vehicles. The other sources of PM emissions are Light-duty vehicles, Heavy-Duty vehicles and Buses with 52 percent of total PM. Because the non-premixed combustion of diesel engine, diesel vehicles lead to particle matters. On the other hand, the number of diesel vehicle in pre-Euro class, which has no particulate filter, is approximately 34,5 percent of total diesel passenger cars due to the late transition to Euro Standards.

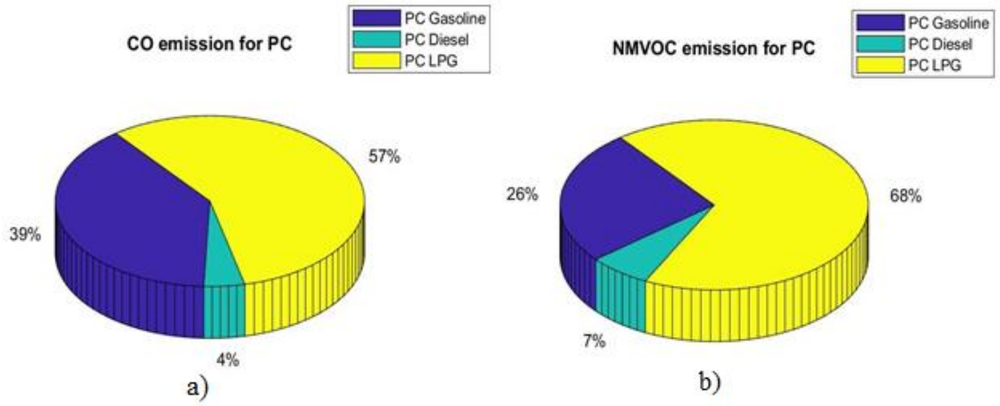

Figure 5. a) Ratio of CO emissions released by passenger cars. b) Ratio of HC emissions released by passenger cars.

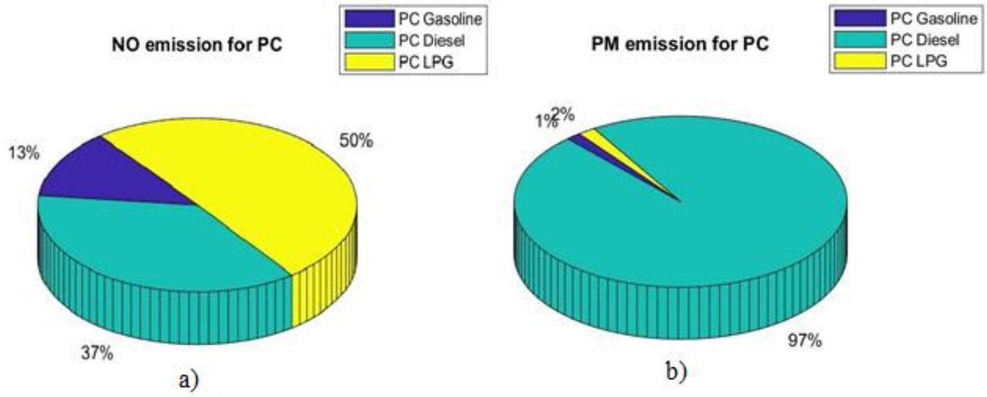

Figure 6. a) Ratio of NO emissions released by passenger cars. b) Ratio of PM emissions released by passenger cars.

The aim of using the Artificial Neural Network (ANN) model considered as a practical approach is to test the ability to predict and exhaust emissions for road transports. Two different training functions were used to provide optimization between the created artificial neural networks models. With using different training functions, the ANN predictions for the output parameters of the exhaust emissions versus the real output data are compared. Levenberg Marquardt and scaled conjugate gradient training functions are used in the ANN. For all exhaust emissions predictions, Levenberg Marquardt algorithm has better prediction result. The predicted versus real values for CO emissions are shown in Fig. 7.

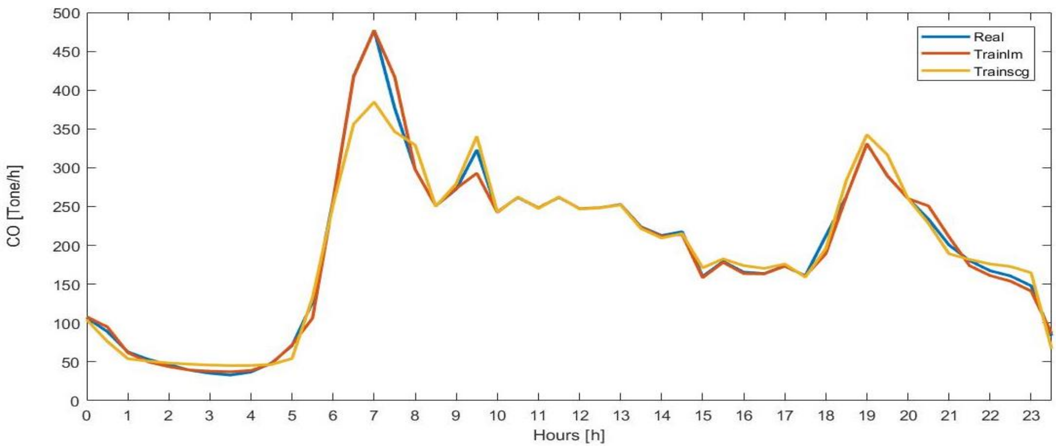

Figure 7. Real and predicted CO emission per half hour in Monday.

When Levenberg Marquardt algorithm (trainlm) used as training function, R value is calculated as 0,9977 but using scaled conjugate gradient training functions (trainscg) R value is calculated as 0,8865. A graph of the predicted versus real values for HC exhaust emission is presented in Fig. 8. For trainlm, the ANN predictions have R value of 0,9916. For trainscg, R is 0,8754. The ANN predictions for the NO emission values versus the real ones are shown in Fig. 9. R value is 0,9812 for trainlm and R value is 0,8845 for trainscg. The ANN-predicted versus real values for PM emissions are drawn in Fig. 10. ANN trained with Levenberg Marquardt training function has R value of 0,9766 but trained with scaled conjugate gradient training function has R value of 0, 8688.All exhaust emissions increased at peak traffic density. As shown in Figure 7,8,9 and 10, when the traffic is density at morning and after work hours, all emissions have peak value at that times.

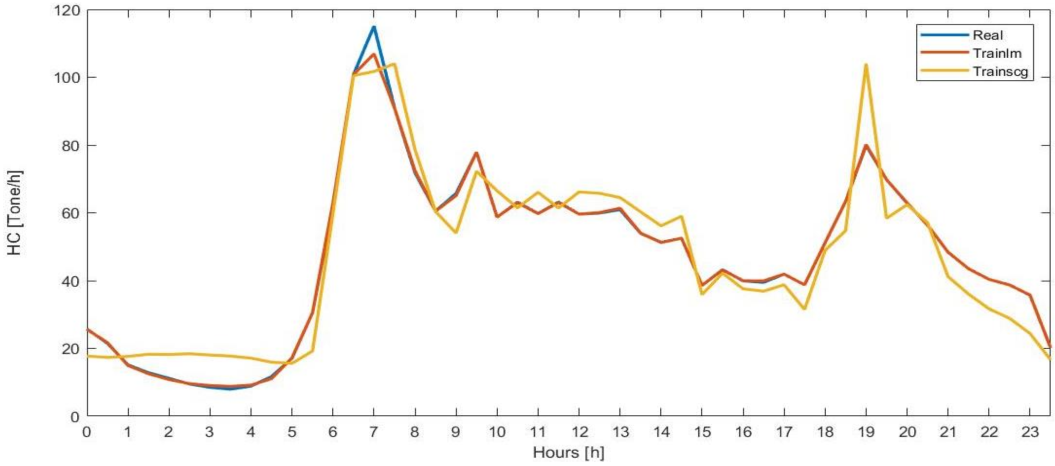

Figure 8. Real and predicted HC emission per half hour in Monday.

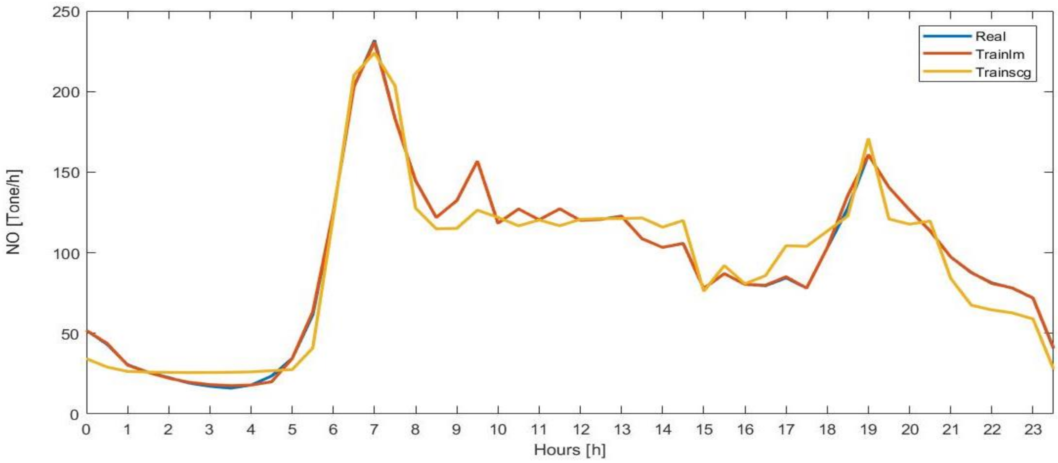

Figure 9. Real and predicted NO emission per half hour in Monday.

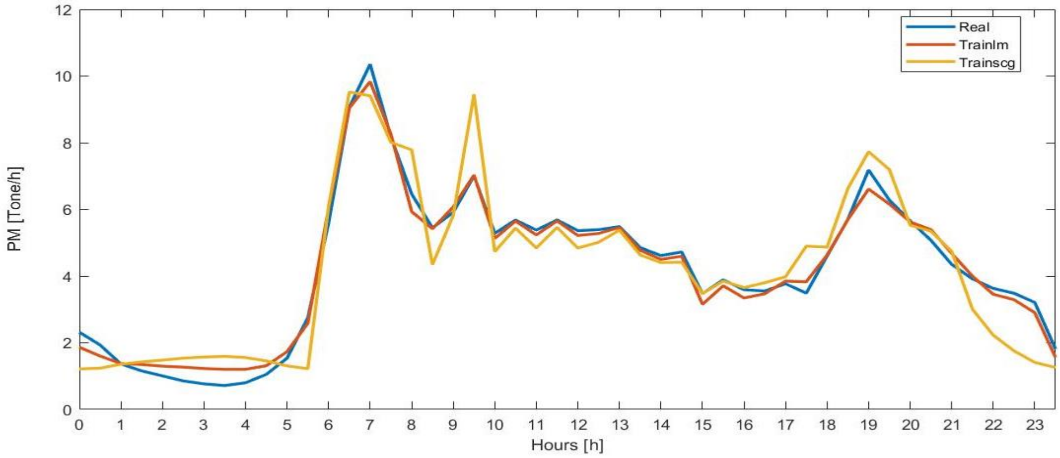

Figure 10. Real and predicted PM emission per half hour in Monday.

5. Conclusion

In this study, with using TURKSTAT and BASARSOFT road transport data, total CO, HC, NO and PM emissions in per time periods are calculated. To calculate the emissions released from road transport, IPCC second approach was used. Then with using MATLAB an Artificial Neural Network was created. Due to the fact that passenger cars represent 66,6 percent of whole fleet in İstanbul, CO, HC, NO and PM emissions of passenger cars compared with respect to fuel types. 96 percent of total CO is released from gasoline and LPG fueled vehicle. Even the LPG fueled engines emit lower CO emissions than gasoline ones, LPG passenger cars cause 57 percent CO of total due to a large number of vehicles. 93 percent of total HC is emitted from LPG and gasoline vehicles. Although LPG fueled vehicle release less HC than gasoline ones, both LPG vehicle number and LPG vehicles converted from old gasoline vehicle are the main reason of HC emissions.

On the other hand, thought the main source of NO emissions is diesel vehicles, quantity of pre-Euro LPG cars plays a major role in terms of total NO emissions. Also 97 percent of total PM emissions of passenger cars released from diesel vehicle, because the characteristics of diesel combustion. This is because of the amount of pre-Euro diesel vehicle which has no particulate filters.

With different training functions, a back propagation (BP) neural network model 3–15–1 (number of input layer - hidden layer - output layer nodes) configuration was developed for predicting exhaust emissions for road transport. Levenberq Marquardt training function has more than coefficient of correlation value 0,9766. This training function has better predictions than scaled conjugate gradient training function. This new approach could be considered as an alternative and practical technique to evaluate the exhaust emissions parameters.

Acknowledgements

This study is supported by BASARSOFT information technology Inc. company. We are grateful to their support about the road traffic data.

Abbreviations

IPCC	International Panel on Climate Change.
NEDC	New European Driving Cycle
EPA	Environmental Protection Agency
FTP-75	Federal Test Procedure
CLRTAP	Convention on Long-Range Transboundary Air Pollution
EC	European Commission
PEMs	Portable Emission Measurement System
WER	Without Emission Regulation
TURKSAT	Turkish Statistical Institute
PC	Passenger Car

CO	Carbon Monoxide
HC	Hydrocarbons
NMVOC	Non-Methane Volatile Organic Compounds
NO	Nitrogen Oxide
PM	Particulate Matter
ANN	Artificial Neural Network
Trainlm	Levenberg Marquardt Training Function
Trainscg	Scaled Conjugate Gradient Training Function
BP	Back Propagation

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