DEVELOPMENT OF AN ANN TO ESTIMATE TRAFFIC EMISSIONS IN ATHENS, GREECE

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INTRODUCTION

In the present study, the 15-min traffic data collected simultaneously at eight main avenues in the city of Athens were presented. The data refers to the vehicle category and vehicle speed. Using the aforementioned data as input, we applied the CORINAIR methodology to estimate emissions of four major pollutants (CO, Benzene, NO_X and PM_{10}) in these eight avenues. The results reflect the daily variation of the aforementioned pollutants. Based on the above data, a Neural Network model was developed. The Neural Network introduced here seems to perform adequately in calculating emissions of CO, Benzene, NO_X and PM_{10} while the validation of the model showed that the corresponding error (calculated vs Observed values) was lower than 3%. The NN model developed in this work seems to be a reliable methodology to calculate road traffic emissions in a complex busy avenue environment.

Traffic data

The traffic data used in this paper were collected from eight main avenues in the city of Athens. Specifically we measured the speed and traffic flow of seven main vehicles categories (catalytic passenger vehicles, non catalytic passenger vehicles, diesel passenger vehicles, light duty vehicles, heavy duty vehicles, buses and motorcycles) in a ten hours basis, from 7:30 to 17:30, classified every 15'. These are the hours that traffic load is heavy and the emissions are in high levels compared to the rest of the day. The aforementioned avenues are representative of the whole urban area and a wide range of traveling speeds and traffic flows is included. Some of the results of speed-traffic flow measurements are presented in Table 1. All represented flows are in vehicles /15 minutes.

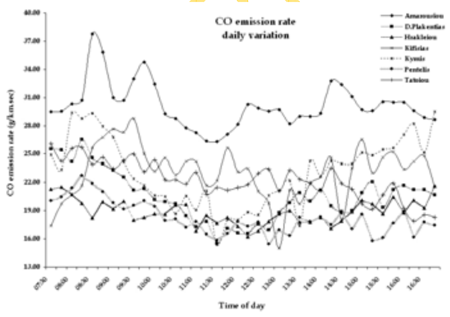
Table 1. Maximum, minimum and average value of traffic flow and speed per vehicle category.

		Catalytic	Non	Diesel	Light	Heavy	Motorcycles	Speed
	max	122	63	11	11	16	23	14
Amarousiou	min	63	12	1	2	2	1	7
	average	91	31	6	6	10	12	10
	max	172	72	14	16	17	21	15
Amarousiou	min	78	18	6	6	2	6	8
	average	113	36	10	12	9	14	12
	max	242	74	11	4	34	8	36
D.Plakentias	min	83	28	3	0	9	4	16
	average	141	48	6	2	22	6	25
	max	242	109	15	9	32	18	34
D.Plakentias	min	83	26	7	0	17	6	18
	average	167	56	10	1	25	11	25
	max	173	64	35	24	24	32	36
Hrakleiou 1	min	76	12	7	3	6	11	17
	average	116	39	23	12	13	21	24
	max	115	54	22	19	14	17	36

Hrakleiou 2	min	63	16	4	5	1	5	23
	average	85	34	9	11	7	10	29
	max	463	207	74	47	22	123	45
Kifisias 1	min	254	78	14	7	4	43	25
	average	368	140	46	24	15	93	31
	max	587	283	87	61	33	168	37
Kifisias 2	min	262	20	24	17	3	48	17
	average	423	163	53	38	18	115	24
	max	339	209	15	27	49	50	44
Kymis 1	min	114	40	2	10	15	12	18
	average	206	88	7	19	31	29	28
	max	318	169	19	36	49	49	39
Kymis 2	min	85	28	2	5	10	7	11
	average	208	87	8	23	32	21	18
	max	195	96	21	21	17	21	36
Pentelis 1	min	105	31	4	4	1	3	21
	average	145	58	12	10	8	11	28
	max	174	82	27	25	22	32	40
Pentelis 2	min	74	27	5	1	6	11	18
	average	131	54	14	11	12	20	31
	max	136	46	12	21	26	21	37
Tatoiou 1	min	44	20	1	3	1	3	13
	average	85	31	5	8	12	9	22
	max	183	65	19	25	30	47	25
Tatoiou 2	min	98	30	3	6	5	8	15
	average	132	50	12	16	19	29	20

Emissions calculation

Emissions place a significant role for the knowledge of the sources of air pollutants and for abatement air quality strategies. In the recent years, the most significant source of pollutants is road traffic (Sturm et al., 1997). Given that the air pollutants concentrations are strongly correlated to the emissions, the estimation of the daily variation of the road emissions is in great interest. In the present study, the above traffic data were used to calculate the emission rate of four pollutants (CO, NO_X, Benzene, PM_{10}) with major environmental and health interest. Emissions rates were calculated by the COPERT (Ntziachristos et al, 2000) methodology, and the results are presented in Figures 1a-1d.



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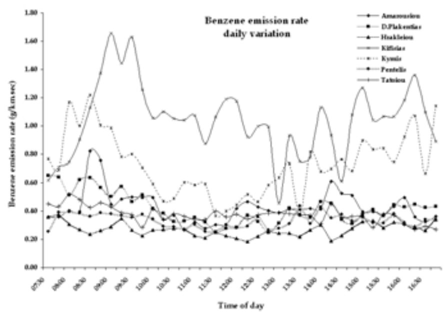

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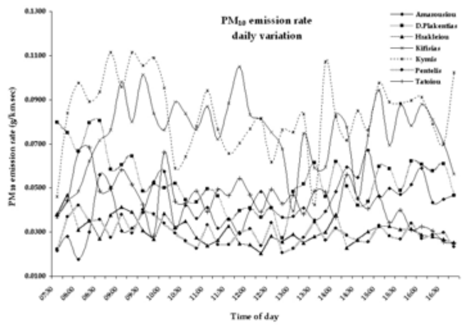
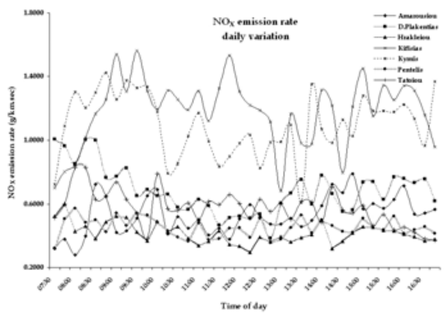




1c **1d**

Figures 1 a-d. Calculated emissions rates using the COPERT methodology

Development of an Artificial Neural Network tool to calculate road emissions

Intending to apply a faster and easier way to calculate vehicles emissions, we developed an Artificial Neural Network. We used traffic speed and vehicle's category traffic flow as input parameters, to predict the emission rates of the four aforementioned pollutants (output parameters). In their general form, Artificial Neural Networks (ANNs) refer to a parallel model architecture able to perform numerical calculations based on distributed processing. ANNs are composed from artificial neurons that operate according to a specified *transfer function*. The neurons interact also with each other through the use of neuron connections called *weight factors* or simply *weights*. Positive or negative weights correspond to connections that propagate or suspend, respectively, signals from other neurons. ANNs can be trained to perform a particular function by adjusting properly the values of these weights.

The process of learning in ANNs constitutes a means of dynamic representation of codified information in the ANN neurons. In particular, *supervised learning* aims at minimizing an *error*, or *cost*, *function* using certain training algorithms that employ first or/and second order partial derivatives. A common approach for numerically calculating the partial derivatives of the error function, *E*(**w**), is the *backpropagation* algorithm [1]. According to this training algorithm, the partial derivatives of **w** are estimated for each input pattern (training prototype), where **w** denotes the function parameters, i.e. the network weights. This means that in the general case where there are *M* weights and *N* prototypes, an $M \times N$ matrix with partial derivatives should be calculated. It should be noted, that backpropagation is an iterative algorithm, thus the above $M \times N$ matrix, is calculated at each step during training. As for the weight adjustment, it is performed according to the following formula:

$$\mathbf{w}_{i+1} = \mathbf{w}_i - \alpha_i \nabla E(\mathbf{w}_i)\,, \qquad (1)$$

where α is a parameter that delineates the ANNs learning rate and *i* denotes the number of iteration steps.

The utilization of the second order derivatives is realized with the calculation of the Hessian matrix, $\nabla^2 E(\mathbf{w}_i)$, which has great theoretical and practical value. Based on the Hessian matrix, more sophisticated training algorithms can be applied [2,3] while the data are organized in a way so that unnecessary calculations are avoided, since the estimation of the Hessian matrix includes iterative calculations of the same terms [4,5].

In our approach we employed a feedforward network architecture which is widely used in ANN applications. This is a multilayer architecture, meaning that the artificial neurons are organized in layers. Typically, a standard feedforward ANN has an input layer, where data are introduced to the ANN, one or more hidden layers, where processing is realised, and an output layer, which generates the final results. Another important characteristic of feedforward ANNs is that neuron activation (or signalling) propagates towards one direction only and specifically from the input layer to the hidden layers and finally to the output layer. The proposed ANN model uses three layers as shown in Fig. 1. The first (input) layer consists of seven neurons, one for each input parameter. Heavy duty vehicles and buses were unified to one input parameter (named heavy diesel vehicles), in order to improve ANN results, given that these two vehicle categories have similar emissions factors. The second (hidden) layer consists of 20 neurons that implement the hyperbolic tangent sigmoid transfer function. This function generates outputs between -1 and 1 as the neuron's net input goes from negative to positive infinity and is more appropriate for ANN applications on function approximation. It should also be noted that the input parameter values are pre-processed in order to be normalized so that the inputs and targets will fall in the interval [-1,1]. As for the number of the hidden neurons, various architectures were tested (different numbers of neurons and hidden layers) but the choice of one hidden layer with 20 neurons provided constantly the higher results. Finally, the third (output) layer consists of four linear neurons that correspond to the four predicted emission rates. Network training was performed using the Bayesian regularisation algorithm [6,7]. This is a supervised learning method that determines the optimal network parameters in terms of model generalisation. These parameters, namely the weights and biases of the network, are assumed to be random variables with specified distributions. The (regularization) parameters are related to the unknown variances which are associated with these distributions. Consequently, based on statistical techniques these parameters can then be estimated.

Within this framework the following error function is minimised:

$$E = a_1 \sum_{i=1}^{N} (t_i - o_i)^2 + a_2 \sum_{i=1}^{M} \mathbf{w}_i^{\,2} , \qquad (2)$$

where t_i are the desired network outputs, o_i are the network outputs during training, $\mathbf{w}_i$ are the network parameters (weights and biases), M is the number of those parameters and N is the number of the training patterns. The hyperparameters a_i are estimated at each iteration according to the following formulas:

$$a_1 = \frac{N - \gamma}{2\sum_{i=1}^{N} (t_i - o_i)^2} , \qquad (3)$$

$$a_2 = \frac{\gamma}{2\sum_{i=1}^{M} \mathbf{w}_i^{\,2}} , \qquad (4)$$

where γ is the number of effective parameters and is given by:

$$\gamma = N - 2a_2 \operatorname{tr}(\mathbf{H})^{-1} , \qquad (5)$$

with $\mathbf{H}$ being the Hessian matrix of the error function and can be approximated as follows using the Jacobian matrix, $\mathbf{J}$, that contains the first derivatives of the network errors with respect to the weights and biases:

$$\mathbf{H} = \mathbf{J}^T \mathbf{J} . \qquad (6)$$

The network parameters $\mathbf{w}_i$ are updated according to the Levenberg-Marquardt optimisation method:

$$\mathbf{w}_{i+1} = \mathbf{w}_i - \left[\mathbf{J}^T \mathbf{J} + \mu \mathbf{I}\right]^{-1} \mathbf{g} \qquad (7)$$

where $\mathbf{I}$ is the unit matrix, μ is a scalar parameter [8] and $\mathbf{g}$ is the gradient which can be computed as:

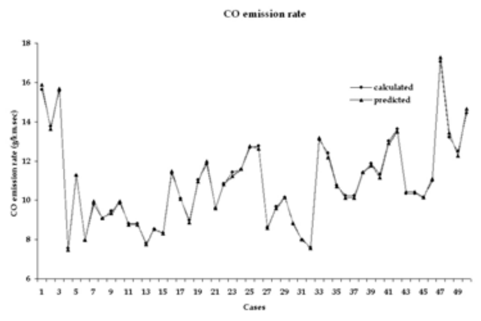
$$\mathbf{g} = \mathbf{J}^T \mathbf{e} \qquad (8)$$

with $\mathbf{e}$ being the vector of network errors.

The network parameters are initialised using the Nguyen-Widrow method [9] and the two hyperparameters, a_1 and a_2, are initially set to one and zero, respectively. Apparently, the error function E is adapted at each iteration, since the hyperparameters a_i are reestimated. According to the Bayesian regularization algorithm the training procedure is considered to be completed when the effective number of parameters, γ, has converged, indicating that the ANN has generalised and not overfitted the training data.

For training and testing the proposed ANN model the overall dataset was randomly divided in two separate sets. The first set, namely the training set, was consisted of 482 samples while the second one, the test set, from 50 samples.

Furthermore, other training algorithms, besides Bayesian regularisation, were also studied. Specifically, we tested the resilient backpropagation [10], the scaled conjugate gradient [11], the BFGS quasi-Newton [12], the one step secant [13] and the Levenberg-Marquardt [8]. However, in all cases Bayesian regularisation proved to be more consistent and robust concerning the generated results (Figures 2a-2d).



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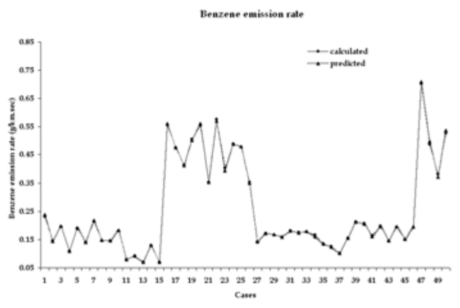

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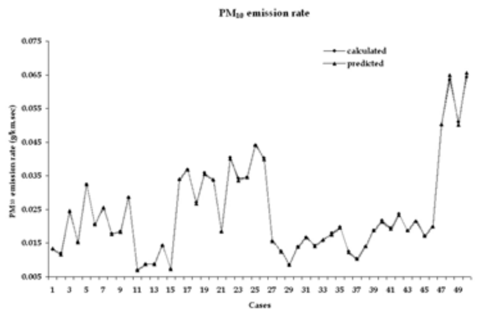

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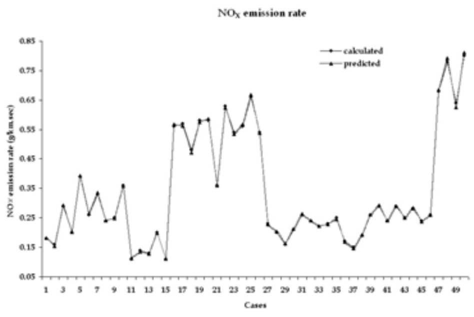

2d

Figure 2. Emission rates for the four pollutants using the ANN (predicted vs observed).

Conclusions

In the present study, some suggestively traffic flow patterns in the city of Athens were presented. After that, the emission rate of four major pollutants was calculated through the COPERT methodology. An Artificial Neural Network was developed to calculate emissions rate of four major pollutants. Emissions calculation is of great importance, because of the direct association among them and urban air quality. ANN emission model is a valuable tool for environmental purposes, having the advantage that emissions prediction may be achieved, in an easier and faster way than COPERT methodology, with an error less than 3%.

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