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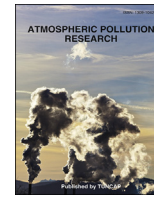

Original article

Forecasting traffic-related nitrogen oxides within a street canyon by combining a genetic algorithm-back propagation artificial neural network and parametric models

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ABSTRACT

A human-built urban street canyon is typically characterized by the presence of buildings on both sides of a road in which the air pollutants, especially those resulting from road traffic, may pose a potential threat to human health. Artificial Neural Network (ANN) differs from parametric model in that it is trained to learn a solution rather than being programmed to model a specific problem with a normal way. Therefore, they would be able to offer better practical skill to predict pollutant. Because pollutant distribution is often greatly influenced by the terrain and meteorological factors, establishing ANN has to consider effective parameters as the input neurons. In this study, traffic-related nitrogen oxides was predicted by combining a genetic algorithm-back propagation ANN and two parametric models (STREET model and OSPM model). This study took those independent parameters or components in the two parametric models into account as the input neurons. These input neurons are likely to enable ANN to reach desire simulation accuracy. Results indicated that ANN had better performance than the parametric models. Further study illustrated that the simulation had higher squared Pearson correlation coefficient (R^2) up to 0.73 for validation, less simulation error, and better trend description in measured data than measured mean. Overall, this study allowed the use of ANN as a viable option for forecasting the traffic-related air pollutants within a street canyon.

1. Introduction

The concentration of pollutants, especially those resulting from motor vehicles within an urban street canyon has received wide attention. Due to the increase in the traffic emissions and buildings on both sides of the roads, higher pollution levels are always observed. The micro-scale dispersion models can be used to assess street canyon air quality in order to provide the support of decision-making for the pollution control strategies and traffic planning (Vardoulakis et al., 2003). The models primarily consist of parametric model and numerical model. Among them, the numerical model could be employed to describe fluid dynamics, mass transfer, chemical reaction and fluid dynamics, etc. (Murena et al., 2009; Bottillo et al., 2014; Madalozzo et al., 2014). However, professional knowledge and operational techniques for user are needed and in addition, they are not cost-effective. In contrary, the parametric models, such as STREET model (Johnson et al., 1973), CAR model (Den Boeft et al., 1996), Canyon Plume-Box Model (CPBM) (Yamartino and Wiegand, 1986), Danish Operational Street Pollution Model (OSPM) (Berkowicz, 2000; Hung et al., 2010), were developed toward simpler operation and less expensive. These

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models have been successfully applied to various street canyons. However, they are needed to search for better solution in order to achieve a desired simulation accuracy suitable for different street canyons during practical engineering application (Assael et al., 2008), which is not an easy process.

In order to obtain better practical skill in fitting air pollutants, Artificial Neural Network (ANN) would be a viable option because they can perform a machine learning and pattern recognition by mirroring brain functions like black model in hope of capturing an underlying relationship between input and output (Maier et al., 2004; Mohanraj et al., 2012). Therefore, it differs from parametric model because they are trained to learn a solution rather than being programmed to model a specific problem in a normal way. As illustrated in previous report, it could offer an alternative approaches to tackle the complex and ill-defined problems (Mellit et al., 2005). Further studies have been investigated by forecasting the pollutants including particle matter with aerodynamic diameter less than 10 μm (PM_{10}) and total suspended particles (TSP) concentration (Paschalidou et al., 2011; Ul-Saufie et al., 2011; Perez, 2012; de Gennaro et al., 2013; He et al., 2014). Other pollutants, such as carbon monoxide (CO), nitrogen dioxide (NO_2), nitrogen monoxide (NO), nitrogen oxides (NOx), sulphur dioxide (SO_2), ozone (O_3), $PM_{2.5}$, and benzene (Karakitsios et al., 2006), were used in literature (Ruiz-Suarez et al., 1995; Martin, 2011; Prakash et al., 2011; Barmpadimos et al., 2012; Xie et al., 2012; Arhami et al., 2013). Overall, these researches have paved the way for reliable use of ANN to calculate pollutants. However, there were no available technical supports for fitting street canyon pollutants at present using ANNs. Therefore developing an effective ANNs for fitting pollutant problems within an urban street canyon can benefit pollution assessment.

Parametric and non-parametric models both consider that the weather and the air quality variables are often statistically related, whereas compared with some typical parametric models, the computation of the ANN models are fast with automatically learning and the adaptive capabilities, which could handle nonlinearity (Zhang et al., 2012). However, the ANN models have a poor generalization performance compared with the parametric models (Zhang et al., 2012). Because pollutant distribution is often greatly influenced by the terrain and weather factors, establishing ANN has to consider effective input neurons in which those parameters utilized by the parametric models as known to have a better correlation with pollutant would be considered as source of input neurons. Therefore, combining ANN and parametric model was helpful for construction of an effective model for air pollutant prediction.

In this study, two types of genetic algorithm-ANNs called IANN and CANN were developed. A simulation comparison between parametric models and developed ANNs was made. During simulation, Back Propagation (BP) neural network was used of which the local minimum and slow convergence were overcome by genetic algorithm (GA). The criteria of assessing model performance contained squared Pearson correlation coefficient (R^2) and other statistical indexes to reduce insufficient possibly misleading an interpretation of a simulation accuracy (Willmott, 1982).

2. Methodology

2.1. Monitoring site

Chongqing is trading center and economic hub in western China, which is characterized by a unique terrain of rough urban area and many hills as well as numerous of narrow roads. Many human-built canyon streets with tall buildings are on both sides of the street road. An increase in the number of motor vehicles has aggravated the air pollution, especially the NOx, CO, HC and Particulate Matter (Huo et al., 2012). Zhongshan Road is one of the principal roads of Yuzhong district, Chongqing, which primarily consists of three sub-roads (denoted as Zhongshan road 1, 2, 3) with full length of about 3160 m and the ratio of average sides height of the buildings on both of the road to street width being about between 0.5 and 3.0 (Fig. 1). The traffic density on the road was larger and according to statistical analysis, it indicated that the types of the main vehicles were car, bus, taxis, small truck and motorcycle. The average intensity of traffic flow was examined as 3590/h, which was dominated by the number intensity of the bus flow. Three seasonal NOx concentrations (autumn, winter and spring during 2007–2008) were investigated on 80 monitoring sites distributed symmetrically on both sides of the roads. The measured maximum, minimum and mean values of peak hours NO_X concentration during heavy traffic for windward side were 0.87 mg/m^3, 0.08 mg/m^3 and 0.41 mg/m^3, respectively. It also showed that the maximum, minimum and mean values of the NOx concentration for leeward side were 1.63 mg/m^3, 0.14 mg/m^3 and 0.84 mg/m^3, respectively. The measured maximum, minimum and mean values of road wind speed were 1.8 m/s, 0.3 m/s and 0.8 m/s, respectively.

The data for autumn and spring as the training data set was used for calibration and that for winter was considered as the testing set for validation in which the ratio of the calibration dataset to validation was 2:1. The emission factors of the motor vehicles was used for modeling by following the observation examined in 2004 (Ma, 2007).

2.2. Artificial neural network

BP neural network employed in this study was performed via generalization of Widrow–Hoff learning rule to three-layer networks and nonlinear differentiable transfer functions (Deh Kiani et al., 2010). It is a gradient descent algorithm in which the network weights are moved along the negative of the gradient of the function, which consists of the input layer, hidden layer and output layer. Each layer is composed of several neurons, and the neurons in a specific layer is connected with all neurons in the next layer (Svozil et al., 1997). The connection in the network between the ith and jth neuron is characterized by the weight coefficient w_{ij} and the ith neuron by the threshold coefficient b_i (Svozil et al., 1997) in which the w_{ij} reflects the degree of importance of the investigated connection. Each neuron computes a weighted sum of its n input signals, x_i ($i = 1,2 \ldots n$) and then applies a nonlinear activation function to produce an output signal (Svozil et al., 1997; Deh Kiani et al., 2010). If the input vector was defined as $x = (x_1, x_2, \ldots x_j, \ldots, x_n$, n is the number of input units) and the output as $y = (y_1, y_2, \ldots y_k, \ldots, y_p$, p is the number of output units). The non-linear activation function allowed for non-linear mapping of the input space to the network output. The mapping for input layer is $x \to R_i(x)$ as the activation function for the ith neuron of the hidden layer and the output layer $R_i(x) \to y_p$. The output layer value for neuron k was given as the following:

$$\hat{y}_k = \sum_{i=1}^{m} w_{ik} R_i(x) \quad k = 1, 2, \cdots, p \tag{1}$$

where m is the number of hidden units; p is the number of output units; w_{ik} is the weight between the ith neuron of hidden layer and the kth neuron of output layer; $R_i(x)$ is the activation function for the ith neuron of hidden layer.