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Classification of Air Quality in the Urban Eastern Areas of Thailand Related to O_3 and PM_{10} Concentration with Neural Network Technique

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Abstract

This study purposed to classify air quality in the urban eastern areas of Thailand related to O_3 and PM_{10} concentration with neural network technique. Correlation coefficient test was utilized to identify which parameters in the weather associating to O_3 and PM_{10} concentration influenced to the determination of air quality measured in the form of air quality index (AQI). The Multi-Layer Perceptron or MLP was generally neural network scheme applied in such this classification problem then a correct classification rate (CCR) was later evaluated model performance for classification of air quality. The results of study indicated 9 atmosphere parameters affected to concentrations of O_3 and PM_{10} were 6 air pollutant parameters (CO, NO, NO_2, NO_X, HC and CH_4) and 3 meteorological parameters (Pressure, Relative Humidity and Temperature). In addition, the MLP9-5-3 represented with 9 input nodes, 5 hidden nodes and 3 output nodes was able correctly classified the group of air quality with 82.53% and 83.65% of the average CCR for respectively the training and validation data set.

Keywords: Air quality, Air Quality Index, O_3, PM_{10}, Neural network technique

Mathematics Subject Classification: 62-07, 62G35

INTRODUCTION

Air Quality Index or AQI is the number termed for monitoring air quality of any day basing on the five principal pollutants; SO_2, NO_2, CO, O_3 and PM_{10}. The standard level of AQI specified by the Thai Environment Protection Department as the satisfactory air is 100. In agreement of [1], [2], the air quality is divided into 6 categories following the AQI (in number): (1) 0-50 representing good air, (2) 51-100 standing for moderate air, (3) 101-200 counting unhealthy air for sensitive group, (4) 201-300 signifying very unhealthy air, (5) 301-400 and (6) 401-500 representing hazardous air. The problems of two air pollutants, O_3 and PM_{10}, presently become more serious impact on human health than the others in the urban or industrial areas of Thailand particularly in the eastern province as mention in [3], [4]. In Thailand, [5], [6], [7], [8] studied and only concentrated on the prediction of O_3 concentration as well as [9], [10], [11], [12] only emphasized on the prediction of PM_{10} concentration while few research like [13] simultaneously predicted both of O_3 and PM_{10} concentrations in Portugal. Some researches, for examples; [14], [15], [16], [17], turned to classify the air quality in any day by using of AQI. However, it revealed in previous researches that only both of O_3 and PM_{10} concentrations significantly directed to the air quality of any day in Thailand. Therefore, this study was objective to present how well neural network technique could efficiently allocate the air quality in to the right group relating to O_3 and PM_{10} concentrations.

MATERIALS AND METHODS

To classify air quality in the urban eastern areas of Thailand based on O_3 and PM_{10} concentration with neural network technique was following these 3 steps.

1. Identifying which independent parameters in the air associated to the concentrations of O_3 and PM_{10} with the test of Pearson correlation coefficient. The two agents of eastern monitoring stations, the General Education Centre, Mueang District, Chonburi and the Map Ta Phut Health Office, Mueang District, Rayong, in the urban areas of Thailand provided the daily concentration term of each variable for 2,265 observations during 2006-2010. The dependent variables were both concentrations of O_3 and PM_{10} while the concentrations of 15 independent variables contained 8 air quality parameters (CO, NO, NO_2, NO_X, SO_2, HC, CH_4, NMHC) and 7 meteorological parameters (Pressure, Rain, Relative Humidity: RH, Temperature: Temp, Sun Radiation: SR, Wind Direction: WD and Wind Speed: WS). Data was divided into 2 sets for analysis. The training data set was first randomly selected 70% of all data using for model training (1,586 observations). The rest of data called validation data set was signified for suitability of model validation.
2. Determining neural network model utilized for classification of air quality. The Multi-Layer perceptron or MLP was applied with the architecture of 3 or 5 hidden nodes in a hidden layer following a recommendation of [18], [19]. The AQI of Thailand had not ever surpassed 300 in the past so the class of air quality was simply classified only 3 groups associated to the concentrations of O_3 and PM_{10} for this study. As of this reason, the number of output nodes in an output layer was equal to 3 corresponding to the three predefined groups of air quality: (1) The group of good air quality was counted on the O_3 concentration ranged 0-50 ppb. and the PM_{10} concentration varied 0-40 $\mu g/m^3$. (2) The group of moderate air quality was counted on the O_3 concentration ranged 51-

100 ppb. and the PM_{10} concentration varied 41-120 μ g/m^3. (3) The group of unhealthy for sensitive air quality based on the concentrations of O_3 and PM_{10} were greater than 100 ppb. and 120 μ g/m^3, respectively.

The number of input nodes was set equal to the number of independent parameters in the weather relating to the concentrations of O_3 and PM_{10} obtained from the result of step 1.

3. Appraising performance of neural network model with a correct classification rate (CCR), one of generally popular criterions applied in classification problem [20], [21], computed as $CCR = \frac{\sum_{k=0}^{C-1} CC_k}{n}$ where CC_k be the number of correctly allocated observations and n be the number of observation in the considered group.

RESULTS

The results of this study were as follows.

1. The 9 air variables correlated to the concentrations of O_3 and PM_{10} affecting to the AQI were composed of 6 air pollutant parameters (CO, NO, NO_2, NO_X, HC and CH_4) and 3 meteorological parameters (Pressure, RH and Temp) as considering of all rather small P-values of Pearson correlation coefficient tests closed to 0.
2. The MLP model was then determined with the 9 input nodes once the number of air independent parameters obtained from the result of step 1. Therefore, both of MLP of neural network models (MLP9-3-3and MLP9-5-3) were consecutively applied as of Figure 1 and Figure 2.

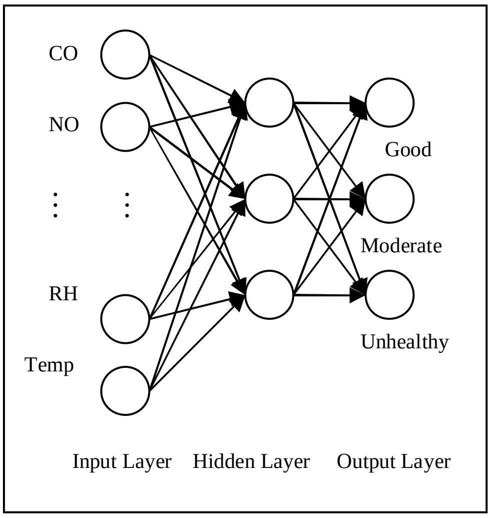

Figure 1: MLP9-3-3

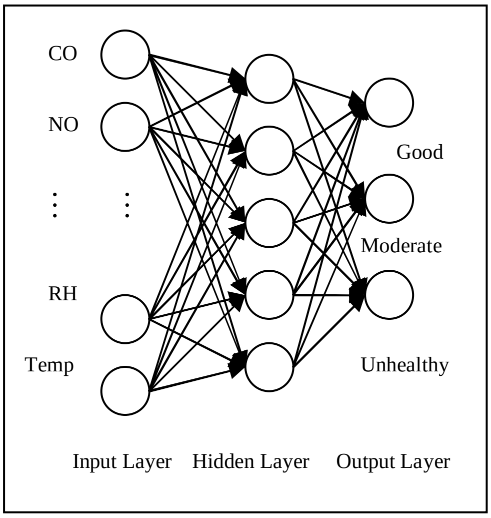

Figure 2: MLP9-5-3

3. Once the two neural network models determined from step 2 were appraised with the CCR and the average CCR, the performances of these two models were shown in Table 1. It indicated the MLP9-5-3 could allocate the air quality into the right group better than the MLP9-3-3 in every condition with the higher values of CCR regardless of data set. Likewise, it would say for overall that the MLP9-5-5 performed the better performance than the MLP9-3-3 with respectively 83.65% and 82.33% of the average CCR for the validation data set.

DISCUSSION

Neural network technique could be potentially applied in classification of air quality group as seeing of the average CCR greater than 80% for both of MLP9-3-3 and MLP9-5-3 models. In addition, these two neural network models did not well allocate for classification in the unhealthy group because (1) there was rather small number of observations in this group (only 20 for training and 7 for validation data set) or (2) the architecture of neural network applied in such of this complicated case might not be appropriate. A better performance would be then performed if (1) there would be more observations of unhealthy group for neural network to remember classification pattern of this such complicated case or (2) the advanced architecture like the Radial Basis Function (RBF) would be trained rather than the simple one (MLP) or adjusting some parameters of neural network, for examples, with more hidden layers or more hidden nodes in a hidden layer.

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Table 1: Performance of MLP9-3-3 and MLP9-5-3 for air quality classification

Model	Data Set	True Air Quality Group	Put into Air Quality Group			Average of CCR
			Good	Moderate	Unhealthy	
MLP9-3-3	**Training**	Good	967	101	0	
		Moderate	184	314	0	
		Unhealthy	2	18	0	
		Total of obs.	1,153	433	0	
		CCR	0.8174	0.7252	0.0000	**0.8077**
	Validation	Good	412	36	0	
		Moderate	77	147	0	
		Unhealthy	1	6	0	
		Total of obs.	490	189	0	
		CCR	0.8408	0.7777	0.0000	**0.8233**
MLP9-5-3	**Training**	Good	978	90	0	
		Moderate	167	331	0	
		Unhealthy	1	19	0	
		Total of obs.	1,146	440	0	
		CCR	0.8534	0.7522	0.0000	**0.8253**
	Validation	Good	413	35	0	
		Moderate	69	155	0	
		Unhealthy	0	6	1	
		Total of obs.	482	196	1	
		CCR	0.8568	0.7908	0.1429	**0.8365**

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