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Original research article

Improvement of PM-10 Forecast Using ANFIS Model with an Integrated Hotspots

Rati Wongsathan[1,*]
[1]*Department of Electrical and Computer Engineering, Faculty of Electrical and Technology, North-Chiang Mai University, Chiang Mai 50230, Thailand*

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ABSTRACT

Due to the situation of increasingly severe PM-10 pollution that adverse affects on humans and environment across the globe, the purpose of this work is to implement the optimal PM-10 forecast model as a basis tool in process of planing/controlling air pollution and public awareness apply to Chiang Mai city and surrounding area, in Northern Thailand. Accurate and reliable forecasting model are our goal. Due to the fuzzy feature of PM-10 as well as the high correlated hotspot during open burning and forest fires season of this study area, the adaptive neuro-fuzzy inference system (ANFIS)-based forecasting model has been statistically implemented as tool for daily mean PM-10 concentration estimation. For achieving more efficient and realistic model, the hotspot count among other meteorological parameters is utilized as the exogenous variable through the design and optimization. The forecasting performance evaluated in terms of the tradeoff between accuracy with regard to RMSE and MAE, computational complexity with respect to the multiplications per an execution, and reliablity through Akaike criterion information (AIC) is used to assess the forecast models. As forecasting results, the proposed ANFIS model with an integrated hotspots outperforms the other existing models.

Keywords: ANFIS; Forecast model; Hotspot; PM-10 pollution

***Corresponding author:** rati@northcm.ac.th
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1. Introduction

Chiang Mai (CM), the largest city in northern Thailand having around 1.7 million people (2017), large agriculture and forest coverage, experienced increasingly severe ambient air pollution related to the particulate matter with a diameter of 10 micrometers or less (PM-10) for a decade. Especially during the high open burning and forest fires season in the period January to April, PM-10 level is frequently exceed the ambient air quality standard (AQI) of 120 μg/m^3. PM-10's sources mainly go beyond local forest fires and biomass burning, and further extend beyond Thailand's border. PM-10 is critical severity for the health of people in this city that literally 60,000 of people were admitted to hospital with various respiratory illnesses (Disease prevention control of CM, 2016).

Since, the PM-10 concentration nonlinearly varies with various factors and depends on locations. Unfortunately, the monitoring devices and permanent stations are insufficient due to the high cost (200,000 USD for construction and 30,000 USD per year for maintenance [1]), for example, in the area 20,000 km^2 of CM only two stations providing. In addition, they could not provide the relation between PM-10 concentration and other related factors. Furthermore, PM-10 is usually measured and officially announced in the daily morning to warn the people but this information may not be thoroughly accessible and cannot prevent people's health in advance. Accordingly, to overcome the stated problems, the PM-10 forecast model should be implemented similar to the weather forecast as a tool for minimizing health risk to the public through online with mobile applications, and others.

In survey research on PM-10 forecast model for CM and surrounding area, most of the existing models preferably used the conventional regression techniques, e.g., simple linear regression [1-2], multi-linear regression [1], logarithm regression [3] and logistic regression [3], due to simplicity and ease of formulation. However, they are not able to capture the PM-10 characteristics at high season that are highly affected by various factors. Autoregressive integrated moving average (ARIMA) model-based PM-10 forecast was presented in [4-7] using some significant time lags of historical PM-10 data as the input. It also performed worst at high season PM-10. Then, ARIMA with exogenous variables or ARIMAX model-based PM-10 forecast [6] is developed using the other correlated toxic gases and related meteorological parameters as the input variables but needs more accurate forecasting improvement. Shortly, various neural network (NN) models as a nonlinear model, i.e., multilayer perceptron NN (MLPNN) [4-5, 8] and radial basis function NN (RBFNN) [8], have been proposed which provide reasonably accurate forecast. However, a number of training data, and an over-fitting are the main drawbacks. To improve this model, the hybrid ARIMA-support vector regression (SVR) [7] and the hybrid ARIMA-NN [4-5] were alternatively formulated. Since the main pattern of the PM-10 problem is nonlinear then the nonlinear transformation using NN should be implemented on the first stage, and the linear residuals are continued to process linearly by the other linear models. Then, the hybrid NN-ARIMA models [5, 9] and the hybrid NN-ARIMAX models [6, 9] are proposed. They outperformed among the rest with regard to the forecasting accuracy. However, a number of system parameters causing computational complexity, design cost and unreliability are disadvantage.

The purpose of this work is to implement the optimal PM-10 forecast model apply to CM city based on adaptive neurofuzzy inference system (ANFIS) by including the number of hotspots as the exogenous variable since it is demonstrated the great impacts of the burning in this area [10]. ANFIS, as the powerful learning of the internal fuzzy rules by NN, is optimized through the experimental design. The performance comparison between the proposed model and the existing models as referred to [4-6, 8-9] are evaluated by the tradeoff between model accuracy using the criteria of mean absolute error (MAE) and root mean squared error (RMSE), computational complexity with regard to the number of multiplications and reliability through Akaike information criterion (AIC).

2. Methodology

2.1 Study Area

CM is located in Chiang Mai-Lamphun basin, where smoke from itself and neighboring Myanmar and Lao is prone to settle (Fig. 1). The hotspots, detected four times daily from the Terra- and Aqua-MODIS satellites, are evident and shown in Fig. 2 against PM-10 with well correlation. Therefore, the basic assumption of this work is that using the number of hotspots as the exogenous variable can improve the forecasting performance.

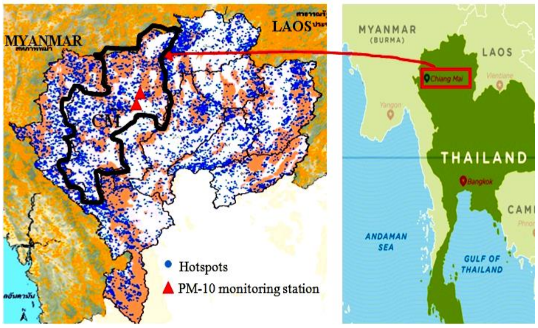

Fig. 1. Study area and a number of hotspots (blue dotted) detected daily from Terra and Aqua MODIS satellites.

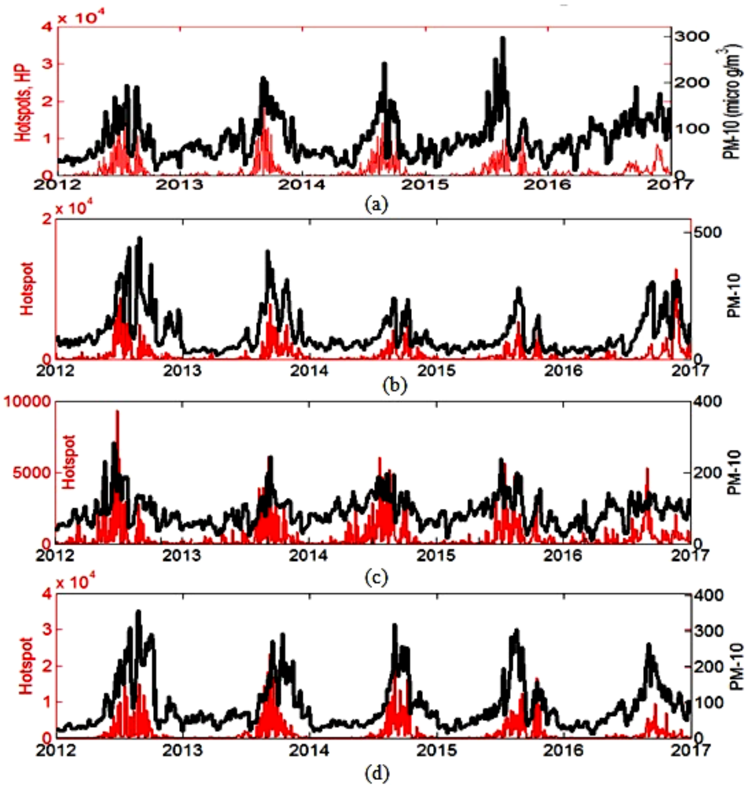

Fig. 2. The relationship between hotspots (red line) and PM-10 (black line) during Jan-Apr, 2012-2017 of (a) Chiang Mai, (b) Chiang Rai, (c) Lampang and (d) Mae Hong Son, Thailand.

2.2 Data Collection and Analysis

In this work, special emphasis focused on PM-10 forecast during a high open burning season which the variations of PM-10 are high and depends on various factors. In the study of [11], the meteorology has a strong impact on PM-10 accumulation in CM. For a past few years, it is evident from the studies of [12-13] that open burning increases the PM-10 level in this area, then the correlated hotspots associated with meteorological variables are introduced as exogenous variables in our proposed forecast model. The positive relationship between the hotspots and PM-10 can be seen in Fig. 2.

The data including the historical PM-10, influenced meteorological variables, i.e., gust wind (*GW*), temperature (*T*), pressure (*P*) and relative humidity (*RH*), and hotspot count (*Hotspot*) within a circle of 150 km radius around the CM city, collected from Thai government PCD and MODIS during 2012-2017 is employed to formulate the forecast model. The descriptive statistics of these variables are presented in Table 1. The entire data is pre-processed and cleared form missing and outlier values to transform into daily average values. It is seen that most of the variables have a wide range of the relative change (ratio of variance compared to range) from 0.43 of *T* to 342 of *Hotspot*. The model based on one rule describing the dynamic change of the inputs probably would not be sufficient to provide the best performance. To verify the statement above, the ANFIS based forecast model is implemented to compare its performance with the other existing models as will be shown later in the next Section.

Table 1. The descriptive statistics of 600 testing data of PM-10 and exogenous variables.

Parameter	Symbol	Unit	Range	Min.	Max.	Mean	Variance	Relative change
PM-10	*PM*	$\mu g/m^3$	260.1	29.9	290	42.65	1065	4.09
Wind gust	*GW*	km/hr	54.7	0	54.7	21.0	44.8	0.81
Temperature	*T*	Celsius	19.8	19.4	39.2	26.7	8.5	0.43
Pressure	*P*	hPa	18.4	964.4	982.8	973.5	11.8	0.64
Relative humidity	*RH*	-	68	24	92	64.9	136.6	2.0
Hotspots	*Hotspot*	point	22,836	0	22,836	1,248	7.8×10^6	342

The coefficients of the correlation between the 6-time lag of historical PM-10 ($PM_t,\ldots,PM_{t-5}$), the meteorological variables and *Hotspot*, and 5-day PM-10 forecast (PM_{t+1}, …, PM_{t+5}) are determined. It is seen from Fig. 3 that the *Hotspot* is positively well-correlated with the forecast PM-10 as well as the other variables. Then, it is considered as one of the tentative exogenous variables for the forecasting model, whereas T_{min}, *Rain*, *WD* and *GW* mean not consideration. To achieve the optimal PM-10 forecast model, the input variable set should contain the fewest significant input variables to describe the PM-10 behavior. The forward selection (FS) method [14] is applied to identify an optimal set of input variables. By this approach, the variable with most significant determining from correlated coefficient is initially analyzed in the beginning through the pilot models, and continued adding other variables to the model as long as its P-value is below some pre-set level. After input selection, the PM-10 forecast model is further optimized.

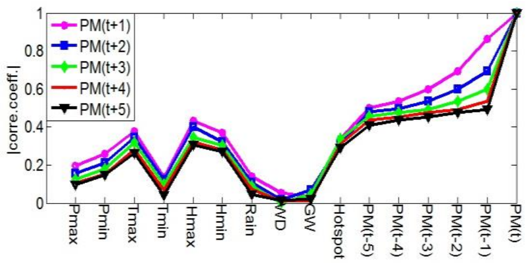

Fig. 3. Correlation of 5-day PM-10 forecast with the tentative input variables.

The model implementations were developed through the MATLAB program and all simulations were run on 2.27 GHz Intel Pentium Core i5 processor with 6 GB of RAM laptop computer. The description of the proposed forecasting models is detailed in the next Sub-Section.

2.3 ANFIS based Forecast Model

Generally, an ANFIS is a fuzzy inference system (FIS) implemented in the framework of adaptive NN. It typically consists of 5 layers in which nodes of the same layer have similar membership function (MF). The ANFIS model illustrated in Fig. 4 using (*P*+1)-significant lag of historical PM-10 data and exogenous variable vector (**X**) including meteorological variables and hotspot counts as the input variables. The single output is *i*-day PM-10 forecast, PM_{t+i}.

The stepwise procedures of ANFIS are as follows,

- Layer 1: The significant input variables obtained from FS method are normalized into the range [-1, 1]. The number of these variables is denoted by N_{Var}.
- Layer 2: Adaptive node consisting of the Gaussian MFs (GMF) computes the degree of MF, $\mu_{PM(t),y},...,\mu_{PM(t-P),y}$, and $\boldsymbol{\mu}_{\mathbf{X},y}$ according to the number of MFs as $N_{PM(t)},\dots,N_{PM(t-P)}$, and $N_{\mathbf{X}}$, respectively, where *y* is the linguistic variable set.
- Layer 3: The number of constructed if-then rules (N_{rule}) equals to $N_{PM(t)}\times\dots\times N_{PM(t-P)}\times N_{\mathbf{X}}$. For the case of first-order Sugeno, the fuzzy rule is shown in the example below:
  Rule i^th: IF PM_t is NB and … and PM_{t-P} is NB and **X** is NB, THEN
  $\theta_i = p_1 PM_t + ... + p_{P+1} PM_{t-P} + \mathbf{p}_{\mathbf{X}}^{\mathrm{T}}\mathbf{X} + p_0$,
  where $p_0,\dots,p_{P+1}$, and $\mathbf{p}_{\mathbf{X}}$ are consequent parameters of fuzzy rule.
- Layer 4: For the rule premise evaluation, the product for *T*-norm is applied resulting the weight values as,

$$w_j = \mu_{PM(t),y} \times ... \times \mu_{PM(t-P),y} \times \mu_{\mathbf{X,y}}\,, \quad (2.1)$$

where $j = 1, 2, \dots, N_{rule}$. The consequence rule evaluations correspond to their weight values are posed to next layer for the implications evaluating.

- Layer 5: The output is calculated using the weight average (WA),

$$PM(t+i) = \sum_{j=1}^{N_{rule}} w_j \theta_j \Big/ \sum_{j=1}^{N_{rule}} w_j\,. \quad (2.2)$$

The outputs of adaptive nodes depend on the adjusted parameters iteratively varied through a hybrid learning rule combining the back-propagation (BP) based gradient descent algorithm and a least-squares method to minimize the objective function,

$$J_i(\mathbf{c},\boldsymbol{\sigma},\mathbf{p}) = \sum_{k=1}^{n} \delta^{n-k} \sum_{j=1}^{N} \left(PM_{t+i,j}^{approx} - PM_{t+i,j}^{actual} \right), \quad (2.3)$$

where *N* and *n* is the number of samples and maximum iterations, respectively, **c**, **σ**, **p** are the column vector of the premise parameters (*c* and *σ*), and the consequent parameters matrix (p_0, p_1,…, p_{P+1} and $\mathbf{p}_{\mathbf{X}}$), respectively.

Remark 1: The proposed ANFIS ([$N_{PM(t)},\dots, N_{PM(t-P)}, N_{\mathbf{X}}$], N_{rule}, 1) model generates $(N_{PM(t)}+\dots+N_{PM(t-P)}+N_{\mathbf{X}})\times 2+(p_0+p_1+\dots+p_{P+1}+\mathbf{p}_{\mathbf{X}})\times N_{rule}$ parameters.

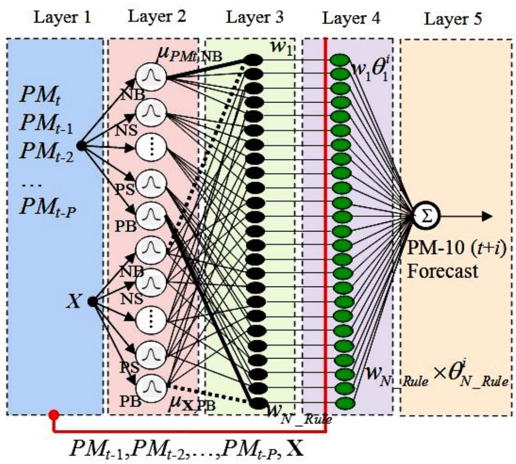

Fig. 4. ANFIS-based PM-10 forecast model.

Remark 2: To further determine computational complexity of the proposed ANFIS, the computing of the degree of GMF, $\exp[-(x-c)^2/2\sigma^2]$, represented by 3-term Taylor series at $x=u$, i.e., $e^{x-u} = 1+(x-u)+(x-u)^2/2+O(x^3)$, where $|x-u|<1$, on the second layer, the computing of fire strength (w) on the fourth layer and the computing of WA (2.2) on the fifth layer provide $(3+2)\times(N_{PM(t)}+\ldots+N_{PM(t-P)}+N_X)$, $N_{rule}\times N_{Var}$, and $(2\times N_{rule}+1)$, respectively. Therefore, the ANFIS model generates total $(N_{PM(t)}+\ldots+N_{PM(t-P)}+N_X)\times5+(N_{rule}\times N_{Var})+(2\times N_{rule}+1)$ multiplications. For the optimization of the ANFIS($[N_{PM(t)},\ldots,N_{PM(t-P)},N_X]$, N_{rule}, 1), the parameters of $N_{PM(t)},\ldots,N_{PM(t-P)}$, N_X, and N_{rule} are selected through the experiment.

2.4 Design of PM-10 forecast model

In this work, the different ANFIS models of i-day forecast are constructed and optimized through the experimental design. The collected data during January-April of 2011-2017 (600 samples) is divided into 3 parts, i.e., training, validating, and testing for 2011-2014, 2012-2015, and 2016-2017, respectively. The input variables including the historical PM-10 for 5-lags (P=4), PM_t, … ,PM_{t-4}, the meteorological variables (P_{max}, P_{min}, T_{max}, H_{max}, H_{min}, RH), and the hotspot are selected through the FS method.

A large number of system parameters and multiplications requiring for ANFIS model resulting from a number of MFs and fuzzy rules can lead to very slow convergence or terminated program. To optimize the ANFIS, the initial number of MFs is set as 5 for each input variables then $y\in\{NB, NS, Z, PS, PB\}$,where NB is negative big, NS is negative small, Z is zero, PS is positive small and PB is positive big. The pilot models are ANFIS_i ([5, 5,…,5], N_{rule}, 1), i=1,2,…, 5. The experimental result of input selection using FS method is shown in Fig. 5. It is seen that two significant variables, PM_t and *Hotspot*, are selected for (1-3)-day forecast and one significant variable of PM_t for (4-5)-day forecast.

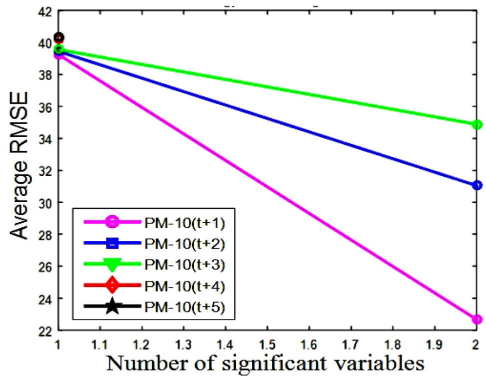

Fig. 5. Input variable selection by FS method.

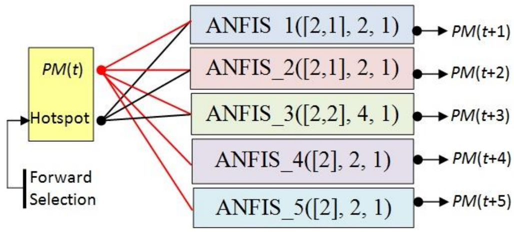

Fig. 6. The optimal ANFIS_i based PM-10 forecast model.

After reducing the number of MFs by one until the error is not improved, the optimal structure of i-day forecast models denoted by ANFIS_i($[N_{PM(t)},\ldots,N_{PM(t-5)},N_X]$, N_{rule}, 1) is illustrated in Fig. 6.

3. Forecasting results and discussion

The (1-5)-day PM-10 forecast results using the proposed ANFIS through the testing and validating data are shown in Fig. 7(a)-(b). The accuracy is satisfied only 1-day forecast, whereas the performance is gradually deteriorates for the others since the instant PM-10 is naturally affected by the current uncertain meteorology variation, unexpected source volume, and others. Then, for 1-day forecast, the forecasting performance of the proposed ANFIS_1([2, 1],2,1) model, single models (Model 1-4) [4,6,8] and hybrid models (Model 5-10) [5,9] are assessed under various criteria, i.e., MAE, RMSE, the number of system parameters (N_K), the number of multiplication per an execution (N_M). It is seen from Table 2 that the proposed ANFIS model performs the best in accuracy. It is able to provide 17-75% more accurate forecast when compared to other existing ten models. To measure the reliability of the models, AIC [15] is applied as a criterion that seeks a model which has a good fit but few parameters. It is defined as,

$$AIC = N_{test} \log\left(\frac{\sum_i e_i^2}{N_{test}}\right) + 2N_K, \qquad (2.4)$$

where e_i is the residuals from forecast, N_{test} is the number of test data. The preferred model is the one with the minimum AIC. From Table 2, the proposed model is the most reliable. Therefore, the proposed ANFIS with *Hotspot* model is indicated as the optimal PM-10 forecasting model tradeoff by several criteria. However, a number of multiplications are the drawback for implementing software.

Table 2. The comparison of forecasting performance between the proposed model and existing models [4-6, 8-9].

Model	Reference	RMSE	MAE	N_k	AIC	N_M
1) ARIMA(4,1,3)	[4]	24.7	16.6	7	96.9	7
2) ARIMA(4,1,3)X(1)	[6]	23.1	15.7	8	91.8	8
3) MLPNN(1,1,1)	[4, 8]	25.4	16.0	4	93.6	5
4) RBFNN(1,2,1)	[4, 8]	25.7	16.0	7	100.8	10
5) *h*ARIMA(4,1,3)-MLPNN(3,1,1)	[5]	25.5	15.3	13	112.2	14
6) *h*ARIMA(4,1,3)-RBFNN(3,2,1)	[5]	28.2	17.9	18	132.7	21
7) *h*ARIMA(4,1,3)X(1)-MLPNN(2,1,1)	[9]	24.6	16.0	13	108.6	13
8) *h*ARIMA(4,1,3)X(1)-RBFNN(4,2,1)	[9]	26.4	15.0	21	131.7	23
9) *h*MLPNN(1,1,1)-ARIMA(1,1,0)	[5, 8]	12.2	8.9	5	19.8	5
10) *h*MLPNN((X[7],3),1,1)-ARIMAX(1,1,0)	[6, 9]	13.8	9.3	14	50.1	18
Proposed ANFIS([2,1],2,1) with *Hotspot*		**7.3**	**5.8**	**12** (c=3, σ=3, p=2×3=6)	**15.3**	**24** (15+4+5)

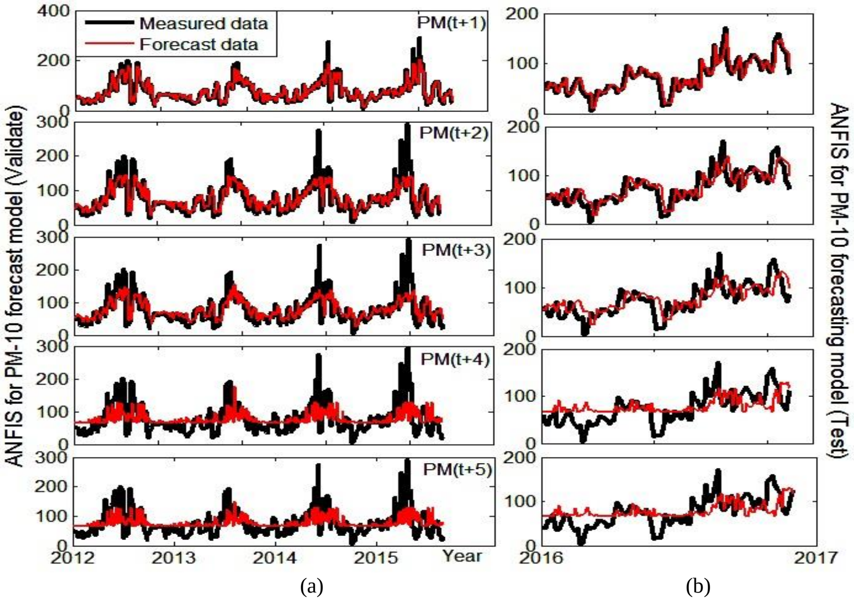

Fig. 7. The results of 5-day PM-10 forecast from the proposed ANFIS model with hotspot counts data for (a) test data and (b) validate data.

To verify the impact of the hotspot counts on the PM-10 (Fig. 2) for the other area nearby CM, e.g., Chiang Rai (CR), Lampang (LP) and Mae Hong Son (MHS), the hotspot counts, including other exogenous variables has been utilized to formulate the ANFIS forecast model through the experimental design similar to CM. CR is the northernmost province and border on Myanmar and Laos which has very high levels of PM-10. For LP, the province that is affected by the air pollution from another sources, especially coal-fired electrical power station in Mae Moh district. For MHS, one of the most beautiful and popular tourism destinations of Thailand, it is most severely affected by PM-10 pollution. It has reached PM-10 level as high as 431 μg/m^3 in 2013.

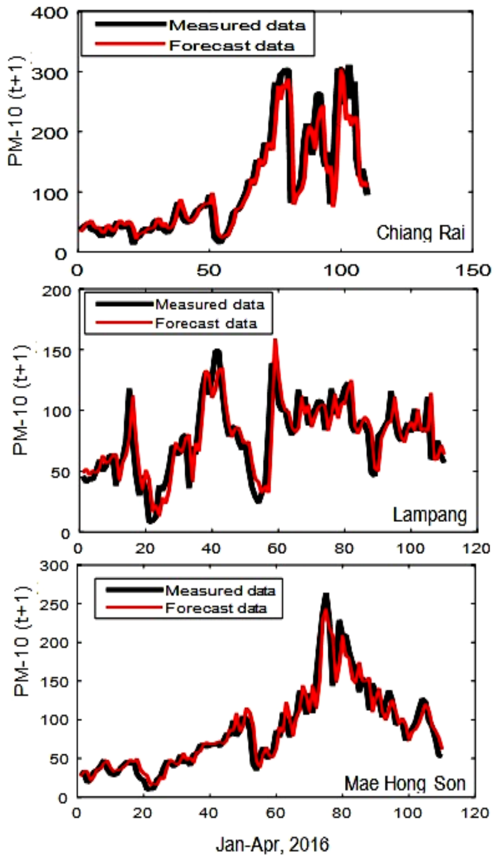

Fig. 8. The PM-10 forecasting results of the proposed ANFIS model with hotspot counts for Chiang Rai, Lampang, and Mae Hong Son.

The ANFIS_1([2,2,1],4,1) model with input variable set of {PM_t, *Hotspot*, H_{max}}, ANFIS_1([2,2,1],4,1) model with the input variable set of {PM_t, *Hotspot*, T_{max}}, and ANFIS([2,2,1],4,1) model with the input variable set of {PM_t, *Hotspot*, P_{min}} are formulated for CR, LP, and MHS, respectively. The forecasting results through the validating data of these formulated ANFIS models for CR, LP and MHS shown in Fig. 8 are quite good. The RMSE and MAE of CR are 28.71 and 21.19, of LP are 17.21 and 13.39, and of MHS are 10.23 and 7.8. It is seen that CR obtained the highest forecast error among others, since its PM-10 level greatly varies and is higher than that of the others.

4. Conclusion

In this work, CM city of Northern Thailand where is located in the high open burning area with critically harmful PM-10 level is selected as a case study for developing PM-10 forecast model. The optimized ANFIS-based PM-10 forecast model is implemented by utilizing the hotspot counts associated with the meteorological variables and historical PM-10 with significant time lag as the exogenous variables. Due to the fuzzy feature of the PM-10 and the high correlated hotspot during high open burning season of the study area, the proposed ANFIS model with an integrated *Hotspot* variable outperforms the other existing single and hybrid models without using the hotspot. As forecasting results, providing high accuracy with regard to RMSE and MAE, and achieving high reliability through the AIC support the above statement. Furthermore, the forecast results obtained from the ANFIS model with hotspot counts for the nearby cities are verified its performance.

To further develop and improve the performance of PM-10 forecast model, the regional online coupled meteorology-atmospheric chemistry or Weather Research and Forecasting with Chemistry (WRF-

Chem) [16-17] is alternatively interesting choice since it was successful in effective and reliable forecasting PM-10 in many areas [18-20].

Abbreviation and symbol

The full meaning of abbreviations and meaning of symbols used in this study are given in Table 3 and Table 4, respectively.

Table 3. List of abbreviations

Abbreviation	Full meaning
PM-10	Particulate matter with a diameter of 10 micrometers or less
AQI	The ambient air quality standard
ARIMA	Autoregressive integrated moving average
ARIMAX	ARIMA with exogenous variable
NN	Neural network
MLPNN	Multilayer perceptron neural NN
RBFNN	Radial basis function NN
FS	Forward selection method
ANFIS	Adaptive neurofuzzy inference system
FIS	Fuzzy inference system
MF	Membership function
GMF	Gaussian MF
WA	Weight average
BP	Back propagation
MAE	Mean absolute error
RMSE	Root mean squared error
AIC	Akaike information criterion
CM	Chiang Mai province
LP	Lampang province
MHS	Mae Hong Son province

Table 4. List of symbols

Symbol	Meaning
GW	Gust wind
T	Temperature
P	Pressure
WD	Wind direction
RH	Relative humidity
X	Exogenous variable
μ	Degree of MF
Y	Linguistic variable
N_{rule}	The number of constructed if-then rules
p	Consequent parameter
c	Centre of GMF
σ	Width of GMF
N_K	The number of system parameters
N_M	The number of multiplications
e	Residual forecast
N_{test}	The number of test data

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