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Hybrid algorithms based on historical accuracy for forecasting particulate matter concentrations

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ABSTRACT

Air pollution has become one of the most significant problems impacting human health. Particulate matter (PM) 2.5 is usually used as an identifier of the intensity of the pollution. The PM2.5 forecasting is essential and gainful for reducing health risks. The efficient model for forecasting PM2.5 concentration can be used in determining the period of outdoor activities, thereby reducing the impact on health. In addition, the government sector can use the forecasting model as a tool for laying down measures a burning control. In this work, the hybrid forecasting algorithms for improving accuracy are presented. The hybrid forecasting algorithms combine neural network models with historical predictive data for improving the accuracy of forecasting. The experimental results show that the proposed algorithms can reduce the mean absolute error and root mean square error of forecasting at 36% and 45%. Therefore, the proposed algorithms are not only effectively used to forecast the PM2.5 concentrations but also apply the lightweight technique based on historical accuracy to forecast other complex problems efficiently.

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1. INTRODUCTION

The air pollution problem has become a significant issue that impacts human health. The pollution problem causes many diseases such as coughing, sneezing, asthma, bronchitis, and lung cancer. Several factors can exacerbate the problem, such as urbanization, industrial plants, agricultural burning, construction, and forest fires. Especially, burning for planting preparation is the most important factor of this problem in the Thailand context [1]. Particulate matter (PM) 2.5 is often used to indicate air quality. Therefore, the development of efficient forecasting and monitoring the PM2.5 concentrations are reasonable solutions for planning and determining measures in the government sector. An efficient forecasting algorithm with high accuracy is still a challenging task. Many previous works have suggested using forecasting methods to predict PM2.5 concentration in time-series prediction [2]. They presented various models of forecasting such as conventional model, artificial intelligence model, and hybrid model to achieve the problem [3]. In addition, the forecasting results were effectively used for planning the duration of the outdoor activities of all people.

The forecasting model is widely used as a tool for planning and monitoring resources usage. The model also applies to increase the ability to decision-making in various areas such as financial, marketing, network, energy, and environment. Several approaches to achieve the forecasting problem are grouped into the following models: conventional models, artificial intelligence models, and hybrid models. The conventional model is classified into two main groups: statistical methods and deterministic methods. The traditional statistic can achieve to solve linear and non-linear problems with high accuracy [4]–[6]. Some approaches efficiently attain the forecasting problem, such as non-linear regression [7], [8], autoregressive integrated [9]–[11], extended Kalman filter [12], and exponential smoothing [13]. The conventional model of a deterministic approach is another approach that does not require historical data, but these approaches need sufficient basic information [14]. The deterministic model is often applied to estimate the degree of pollution problem accurately [15]. The statistical approach delivers more accuracy of long-term forecasting than the deterministic approach, although those approaches need more computational resources than others. The statistical method generally requires a lot of historical atmospheric data that have extreme dependencies on a specific site. Therefore, the statistic approach forecasts the pollution concentrations accurately. Many efficient techniques, for example, artificial intelligence and hybrid method, are often applied to enhance the accuracy of forecasting.

The artificial intelligence model attains to the weather forecast and air quality prediction with high accuracy. This approach consists of artificial neural networks [16], [17], machine learning [18], [19], deep learning [20], [21], evolutionary methods [22]. This approach does not only give better forecasting accuracy than mathematical methods, but it also consumes computing resources lower than the conventional approach. This approach can solve highly complex problems that are difficult to construct the theoretical models. Thus, artificial intelligence (AI) is widely applied to achieve a forecasting problem of a complex system such as PM2.5. Many previous works studies forecasting PM2.5 technique based on artificial neural network (ANN) approach including recursive neural network [14], fuzzy neural network [23], convolutional neural network (CNN) [24], back propagation neural network [25], and adaptive neural network [26]. However, the ANN technique achieves the local optimum problem and the global optimum problem [27]. AI with evolutionary algorithms is one of the attractive approaches to forecasting problems such as particle swarm optimization(PSO), and genetic algorithm (GA) [28]–[30].

The hybrid forecasting model is the primary approach to improve the performance of forecasting in various fields. This approach is not only used to accomplish a long-term nonlinear problem, but it also enhances forecasting accuracy with the same performance as the other methods mentioned above. The previous works studied the hybrid technique includes cluster-based [31], ANN and multiple linear regression [32], ANN and k-means clustering [33], ANN and wavelet [14], back propagation ANN (BPANN) and wavelet [34], BPANN and adaptive differential evolution [27], deep learning and wavelet [34], recurrent neural network (RNN) and long short-term memory (LSTM) [35], multi-objective Harris hawk's optimization (MOHHO) [36]. The hybrid models can help to enhance the accuracy of PM2.5 prediction and the model also achieve the limitation of single-site prediction to generalized [37]. The hybrid approach [38] can also be applied to forecasting complex problems in other fields.

The proposed algorithms of forecasting are implemented based on historical prediction. The forecasting algorithms combine traditional neural network prediction in the first step, and the prediction result from this step has enhanced the accuracy of the result in the second step. In the improving accuracy step, the forecasting performance obtains from comparing the predictive data of the neural networks to the real measurement value. These performances are used as the weighted factor to improve the accuracy of final forecasting. The experimental results showed that the proposed algorithms can improve the accuracy from the traditional approach significantly. The main contributions of this work are as: i) The hybrid forecasting algorithms are proposed to increase the predictive accuracy using the historical prediction technique; and ii) The use of the lightweight technique applied with conventional artificial intelligence can efficiently improve the accuracy of forecasting problems.

2. METHOD

The algorithms proposed in this work utilize the benefits of neural networks for complex systems based on historical forecasted data, consisting the lightweight techniques to improve forecast accuracy. This technique can be applied to conventional time-series data. There are models used in this research consisting of the data model, multi-layers perceptron of the neural network, proposed algorithms, and performance evaluation model. The detail of each model is addressed as follows.

2.1. Dataset description

The dataset of PM2.5 concentration used as the main factors, included temperature, dew point, humidity, and wind speed, affecting PM2.5 levels in Chiang Rai province, the northern province of Thailand, were collected from BerkeleyEarth and WeatherUnderground from 2017 to 2020. Chiang Rai is an agricultural city encountering severe smog, especially in the planting season over the past decades. This study used data collected daily over three years. Those data are divided into two parts: i) learning data set from 2017 to 2018, and ii) testing data set from 2019 to mid-2020. This set is used to evaluate the forecasting performance of the proposed algorithms.

2.2. Neural network model

In this work, we apply the neural network model based on a multi-layer perceptron (MLP) neural network. The multi-layer perceptron model can deliver efficient results with non-linear problems and also work well with large input data. Normally, the neural network model is characterized by three main layers: input layer, hidden layer, output layer. The input layer is used as the layer that obtained input parameters from the external environment. Next, the hidden layer is the middle part of the neural network in which this layer may be composed of several hidden layers. In this layer, the weighted value of each factor affecting the forecast value is calculated. The output layer performs as a node for collecting all the results from hidden layer before submitting the solution. The neural network model applied in this work shown in (1). The input layer of the model uses set (X) as the input parameters, consisting of (x_i) represented by each factor for processing in the learning process.

$$Y_i = \sum_{j=1}^{N_l} w_{ij}^l H_j^l + \beta_i \tag{1}$$

The predicted value (Y_i) is calculated by the combination of the weight (w_{ij}^l) of the hidden node (j) of the layer (l). Next, this layer sent the output to hidden nodes (i) of the next layer and bias (β_i) of hidden nodes (i). Let H_j^l denote the hidden node (j) of the layer (l) can be expressed as $H_j^l = \sum_{i=1}^{N_l} w_{ij}^{l-1} H_j^{l-1} + \beta_i^l$. The hidden layer is recursively computed from weighting (w_{ij}^{l-1}) the previous layer ($l-1$) to the hidden node (j) in the layer (l), and combined with a bias (β_i^l) of the hidden node (i). The H_j^1 (as computed by $H_j^{l-1} = \sum_{i=1}^{N_l} w_{ij}^0 x_i + \beta_j^1$) presents the model for each node of the first layer. The node of the first layer (H_j^1) can be applied by weighting (w_{ij}^0) of each input parameter (j) to hidden nodes (i).

An empirical approach is applied to attain the best effort of neural network structure, including the number of hidden nodes and the number of the hidden layer. The experimental settings of nodes in each layer and hidden layers are set of 6-30 nodes and set of 1-4 layers, respectively. We also trained the model with 200 to 1400 training cycles with the number of nodes and the number of a hidden layer as we mentioned above. The best model obtained from the model has a minimum of mean absolute error (MAE). The forecasting model of a neural network based on best-effort testing is consisting four hidden layers, each layer containing 28 nodes. This configured neural network structure is used as a preliminary prediction result to apply those forecasting results to a more accurate prediction by the proposed algorithms presented in this research.

2.3. Proposed algorithms

In this section, the detail of each algorithm applied by the historical prediction technique is described. The algorithms obtain historical predictive data for improving the accuracy of the forecasting. The preliminary result of the neural networks is used as baseline forecasting. Before the final solution is presented, the candidate solution must be improved accuracy with the proposed algorithm as shown in Figure 1. The main concept of the proposed algorithms adopted historical predictive data of both long-term and short-term forecasting. The historical data, obtained by computing relative error from the previous prediction, uses as a weighting factor in the second step.

2.3.1. Coefficient weighted algorithm

The preliminary predictive results of the neural network were considered to calculate the correlation coefficient from the long-term historical data. The correlation coefficient of the measurement data is estimated by the average forecasting performance with a linear regression technique. This algorithm is called the coefficient weighted (CW). The main idea of this method is to attempt to adjust the forecast coefficient each time to 1.0 because the forecast value is closer to the actual measured value. In Figure 1(a), the target of forecasting is equal to $Y_G \cong Y_i$, where Y_G is the goal of the predicted value that needs to be close to the measured value, and Y_i is the predicted result of the neural network. The linear regression is consisting of a regression coefficient ω_t and a correlation ε_t. The relation of ω_t and x_G shown in (2), where x_G is the measured value, $c_t$is the regression coefficient of the trendline and b_t is the correlation of the target prediction. Finally, the improved accuracy of forecast value (Υ_i) is computed by the regression coefficient (ω_t), and correlation (ε_t) that is weighted by the coefficient of the long-term historical accuracy (as shown in (3)). The coefficient weighted (ω_t) is obtained from the inversed regression coefficient $1/c_t$ and ε_t also calculated from the correlation is weighted by the coefficient b_t/c_t.

$$x_G = \frac{Y_i \pm b_t}{c_t} \tag{2}$$

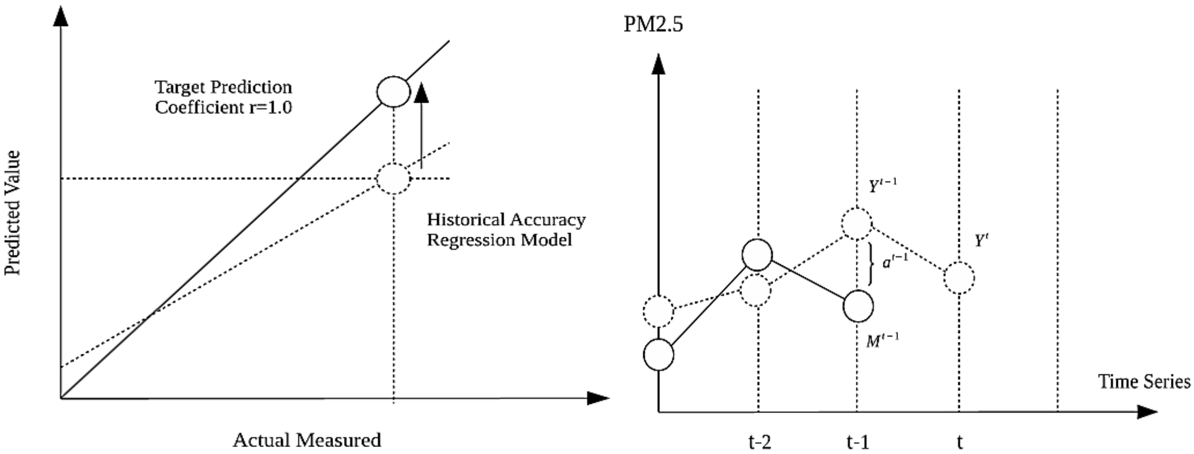
$$\Upsilon_i = \omega_t Y_i \pm \varepsilon_t \tag{3}$$

2.3.2. Latest recently measured algorithm

Next, the forecasting algorithm uses an improved performance technique based on weighting with the recently measured actual data and the previous forecast error. The recently measurement of PM2.5 level is a short-term historical weighting technique. The forecasting algorithm can efficiently predict a PM2.5 concentration in unstable conditions. This proposed algorithm is called the latest recently measured (LRM). As shown in Figure 1(b), the improving algorithm obtains the forecast result (represented by a circle with a dotted line in t) from the last measured value (represented by a circle with a solid line in $\mathrm{t}-1$ and weighting the predicted error from the previous forecasting (in $\mathrm{t}-1$). The improved result Υ^t, as shown in (4), is computed from recently measure of PM2.5 (M^t) and relative error of latest prediction (α^t) (as presented in (5)). The current result of neural network (Υ^t) is weighted by the lastest relative error of forecasting before the final result is presented.

$$\Upsilon^t = \mathrm{M}^{t-1} + \alpha^{t-1}\Upsilon^t \tag{4}$$

$$\alpha^t = \frac{\Upsilon^t - \mathrm{M}^t}{\Upsilon^t} \tag{5}$$



(a) (b)

Figure 1. Concept of the proposed algorithms (a) CW and (b) LRM

2.3.3. Mixed CW and LRM algorithm

The main idea of mixed CW and LRM obtains from the strength of two previous algorithms. Normally, the coefficient weighted algorithm can efficiently forecast the PM2.5 concentration of stable condition. On the other hand, the latest recently measured technique gives more accurate results of forecasting in inclement conditions.

$$\Upsilon^t = \begin{cases} \mathrm{M}^{t-1} + \alpha^{t-1}\Upsilon^t, & if\ \ \mathrm{M}^{t-1} < \epsilon \\ \omega_t Y_i \pm \varepsilon_t, & Otherwise \end{cases} \tag{6}$$

Therefore, we developed the mixed coefficient weighted and latest recently measured to improve accuracy. The algorithm needs to uses the average PM2.5 value (ϵ) in normal conditions as the threshold of result selection as shown in (6). The latest measured (M^{t-1}) PM2.5, compared with the threshold before the forecasting result is deployed, uses as criteria for selecting the solution. In the next section, the experimental results of each algorithm are discussed.

2.4. Performance evaluation model

For forecasting problems, there are many measurement metrics to evaluate the accuracy of the predicted results. The first metric used in this work is MAE. The MAE indicates the absolute difference in mean error between the forecasted values and the actual measured values. It is defined as $MAE = \frac{1}{N}\sum_{i=1}^{N}|m_i - p_i|$. Another measurement metric used for comparing the prediction performance is root mean square error (RMSE). This metric is one of the most frequently used to measure the forecasted values compared to the actual measured value because the metric is highly sensitive to large errors. The RMSE is presented by $RMSE = (\frac{1}{N}\sum_{i=1}^{N}(p_i - m_i)^2)^{1/2}$. N denotes the number of the collected data, p_i is the predicted value, and m_i is the actual measured value. Let $\overline{m_i}$ be the average of the actual measured value. The correlation factor (R^2) is defined as $R^2 = \sum_{i=1}^{N}(p_i - \overline{m}) / \sum_{i=1}^{N}(m_i - \overline{m})^2$. The measurement metric (R^2) applies for indicating the amount of systemic error of the proposed model. In the next section, the proposed algorithms for improving the accuracy of forecasting were presented.

2.5. Example case

In this subsection, the algorithmic details of improving the foresting results are briefly presented. Firstly, we input the factor parameters to the learned model from the configuration described in section 2.1.2. Next, the CW algorithm tested the predictive efficiency of the neural network from the learning dataset to find the correlation coefficient in this example given equal 0.8 (c_t) (thus ω_t was 1.25), and given ε_t=9.5. Given that on day 1 the forecast value from the neural network is 60.5 (Y^t), therefore, after adjusting with (3) of the CW algorithm, the forecast result of PM2.5 concentration is 85.13. For the LRM algorithm, the forecast values from the neural network (Y^t=60.5) are weighted based on the previous forecast error (as shown in (5)), α^{t-1}=0.26, combined with the previous measurement M^{t-1}=83, thus the forecast value of 98.8 (as calculated in (4)). Given that the value ϵ is equal to 44.5, the Mixed CW-LRM choose the solution from LRM as the forecast value. In this case, we have taken an example from a one record of the test dataset, in which case the PM concentration is 94. In the next section, the performance of forecasting of the proposed algorithms are presented.

3. RESULTS AND DISCUSSION

The neural network model was built on Keras, a high-level neural network API running on Tensorflow, and applied the proposed algorithms to improve forecasting accuracy with the discrete-event simulation. The predictive performance of the proposed algorithms is presented in Figure 2. Those performances are obtained by correlating the actual measured value (x-axis value) to the forecast value (y-axis value). The correlation coefficient should be close to 1 (r=1.0), meaning a highly accurate forecast. A testing data set that contains 460 time series, is used to evaluate the effectiveness of the forecast. The experimental results presented in Figure 2 show that the forecasting of the neural network is highly accurate in the PM2.5 range at average levels, but it gives lower accuracy during the PM2.5 is in high range and quite inconstant. The forecast performance of the high range (at the tail of the graph) deviated from the trend line, resulting in the average forecast performance of the neural network with a correlation coefficient of 0.58. Therefore, the proposed CW algorithm is used to adjust the forecast values before giving the final forecast results. The forecast values were adjusted with a new correlation coefficient obtained from the inverse correlation coefficient of the neural network ($1/c_t$) as in (3). The experimental results of the CW algorithm resulted in a 25% higher forecasting accuracy, as it was able to improve forecasts in the unsteady range of high PMs for a short period of time effectively. The experiment results of the CW showed that the forecast, especially at high PM2.5, tends to move closer to the trendline with a relative coefficient of 0.75. However, the concentration of PM2.5 is continuous under normal conditions, observed as the level of PM2.5 may gradually increase or decrease significantly over time. The LRM method prioritizes the most recent measured value while using the previous forecast error to weight the forecast value from neural network. The results of LRM show that it gives a more accurate forecast PM2.5 concentration with a relative coefficient of 0.85. The average forecast results are more accurate from the neural network, CW at 32.5% and 12.7%, respectively. Finally, the experimental results of the mixed CW-LRM, a method that combines the advantages of both CW and LRM for predictive final tuning, are presented. This method uses ε as the criteria for selecting values from previous measured (M^{t-1}). The ε used as a criterion to select the forecast result was computed from the mean of the PM2.5 concentration levels in each area. As a result, selecting LRM forecasts with advantages that can forecast more normal values of the PM2.5 level, the results after mixed CW-LRM have a forecast result with better average forecast accuracy than LRM at 9.4%, with an increase from forecasting with the neural network at 38.9%. In conclusion, all three methods presented require preliminary forecasting data from the neural network, and then the methods can be used to fine-tunes the forecast values to be more accurate. As presented in Figure 3, the time series plot and forecasting performance of each algorithm are presented. The forecasting results of the proposed algorithms that are illustrated with the time series plot, compared to the measurement of PM2.5 concentrations with 460 test data are shown in Figure 3.

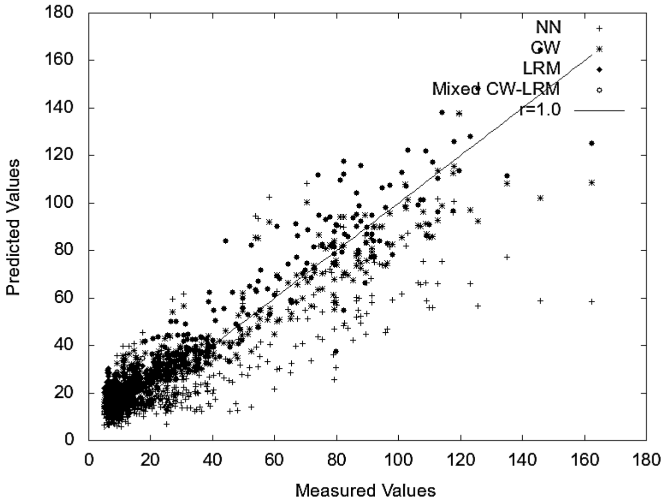


Figure 2. Forecasting results of Neural network, CW, LRM, and Mixed CW-LRM

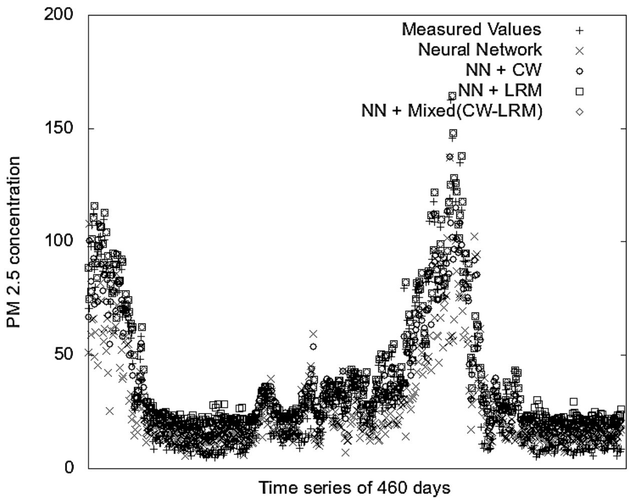


Figure 3. Performance evaluation result of the proposed algorithms

The experimental result of the forecasting accuracy as shown in Table 1, found that the CW algorithm had a better correlation coefficient than the neural network method, but MAE and RMSE were 14.90 and 22.94, respectively, which this algorithm was accurate less than the forecasting accuracy with neural networks. Next, the experimental results of the LRM algorithm show that the algorithm can deliver more forecasting accuracy than the CW algorithm. The use of the latest recently measured algorithm gives MAE and RMSE values are lower at 26% and 45%, respectively, compared to the CW algorithm. The mixed CW-LRM algorithm combines the advantages of CW and LRM algorithms to increase forecast accuracy. The algorithm has an acceptable forecasting performance, and the forecasting results of the algorithm can reduce MAE and RMSE from LRM by 31% and 21% respectively.

Table 1. Error of the proposed algorithms

Algorithm	MAE	RMSE
Neural Network	11.74	17.96
CW	14.90	22.91
LRM	10.95	12.65
Mixed CW-LRM	7.53	9.94

The performance of three proposed algorithms with the MAE and RMSE values are summarized. The MAE values of the CW algorithm, LRM algorithm, and mixed CW-LRM are 14.90, 10.95, and 7.53, respectively. The RMSE values are equal to 22.91, 12.65, and 9.94 respectively as shown in Table 1. Next section, the conclusion of the paper is presented.

4. CONCLUSION

The forecasting model of PM2.5 concentration is challenging research. An efficient model is used to accurately predict the level of PM2.5 for determining the period of outdoor activities. The model also helps the government sector in determining the duration of burning in the harvest season. In this work, three forecasting algorithms, combined with the neural networks based on historical prediction data, are proposed. The results of the traditional neural networks provide the acceptable accuracy of forecasting PM2.5 concentrations with the configuration structure where a minimum MAE value consists of four hidden layers of 28 nodes for each layer. In the improving accuracy step, we propose the CW, LRM, and Mixed CW-LRM algorithm to improve the forecasting accuracy. The correlation coefficients of the three proposed algorithms were 0.75, 0.86, and 0.95, respectively. The MAE and RMSE were downward trends compared to the results of neural network forecasting. The mixed CW-LRM reduced MAE and RMSE at 36% and 45% from the traditional neural network algorithm. Therefore, the proposed algorithms based on historical data can improve forecasting PM2.5 concentration efficiently. For future work, improvement of the learning process is to determine the main factors of neural network prediction that helps to increase forecasting speed and accuracy. The use of evolutionary algorithms is another way for improving accuracy based on self-improvement forecasting.

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