International Journal of Organizational Innovation

$PM_{2.5}$ CONCENTRATION CHANGE TREND FORECAST: TAKING AN ADMINISTRATIVE REGION OF KAOHSIUNG CITY AS AN EXAMPLE

Chun-I Chen*
Department of Industrial Management, I-Shou University
Taiwan, R.O.C.
*corresponding author: EddyChen@isu.edu.tw

Chia-Chin Hsu
Department of Industrial Management, I-Shou University
Taiwan, R.O.C.

Wan-Chin Chen
Department of Industrial Management, I-Shou University, Taiwan
Taiwan, R.O.C.

Ting-Yu Chen
Department of Industrial Management, I-Shou University, Taiwan
Taiwan, R.O.C.

Wan-Ting Chen
Department of Industrial Management, I-Shou University, Taiwan
Taiwan, R.O.C.

Abstract

$PM_{2.5}$ pollution has large negative influence on the human body, and the concentration of $PM_{2.5}$ will change over time under the influences of the emissions of different pollution sources, precipitation, wind speed, and other atmosphere diffusion conditions. With $PM_{2.5}$ concentration data provided by the survey station of the Environmental Protection Administration as the data used for construction of the model, this research adopted the Moving Average Method, Exponential Smoothing and Grey Forecasting Method to construct the model to forecast $PM_{2.5}$ concentration. The research results show that it has the best performance when Smoothing coefficient α is equal to 0.8.

Key Words: Fine Particulate Matters, Simple Moving Average Method, Exponential Smoothing, Grey Forecasting Method

Introduction

Many scholars have pointed out that long-term exposure to air polluted environments with fine particulate matters ($PM_{2.5}$) can cause changes in heart rate and blood pressure, increase the mortality rate of neonates and cardiopulmonary diseases, and have greater impact on respiratory health (Woodruff et al., 2006; Samet et al, 2000). Atmospheric Particulate Matters are generally divided into PM_{10}, $PM_{2.5}$, Dust, Metal fume and its complex, Smoke, Acid mist, and Soot. However, most $PM_{2.5}$ pollutants are mainly formed by the chemical reaction of gaseous pollutants in the atmosphere, their chemical compositions are very complex, and they have different chemical composition characteristics according to the different pollution sources and procedures (Weng, Kuo, and Lu, 2013; Kampa and Castanas., 2008; Shah and Rau,, 1990; Jacobson et al., 2002; Salako et al., 2012; Fruin et al., 2008; Pérez et al., 2010; Invernizzi et al., 2011; Bond et al. 2013; Kulmala et al., 2004; Seinfeldet al., 1998).

According to the analysis results of the air quality model, about 60-66% of the annual average concentration of fine particulate matters $PM_{2.5}$ in Taiwan come from domestic sources, while 34-40% are transferred from overseas, namely, the industrial pollution of adjacent areas, such as Mainland China, Japan, and Korea, which spreads to Taiwan with atmospheric circulation or monsoon. The influence of all kinds of pollution sources in Taiwan on the concentration of fine particulate matters $PM_{2.5}$ is shown in Figure 1 and Figure 2.

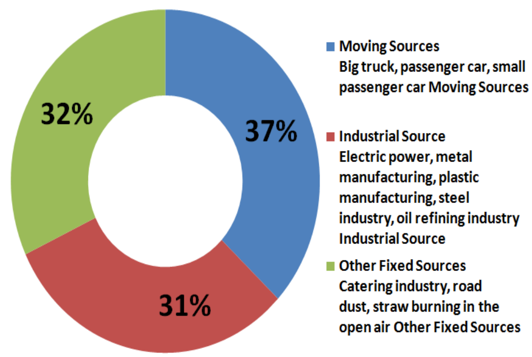

Figure 1. The Influence of All Kinds of Pollution Sources in Taiwan on $PM_{2.5}$ Concentration
Source: Tsai et al. (2017), New Deed of Prevention and Treatment of Air Pollution

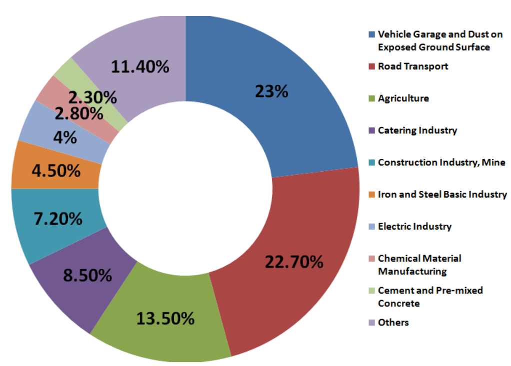

Figure 2. $PM_{2.5}$ Emission Ratio Diagram of Various Pollution Sources in the Whole Country
Source: Air Protection Department, Environmental Protection Administration, Executive Yuan (2015).

Methodology

According to the website of the Environmental Protection Administration of Executive Yuan, this research extracted the $PM_{2.5}$ concentration values of a survey station of an administrative region in Kaohsiung City from January 1, 2016 to December 31, 2016. The Moving Average Method, Exponential Smoothing, and the Grey Forecasting Method were used to construct the $PM_{2.5}$ forecast model, the minimum absolute deviation value was used to evaluate the performance of the forecast model, and finally, the appropriate forecast method was adopted to construct the model. The Moving Average Method adopts stage 2-9, Exponential Smoothing adopts *a* value of 0.1-0.9 in stages 1-12 for prediction, the Grey Forecasting Method adopts the data of February, with linear and nonlinear 4Data, 5Data, and 6Data used for comparison, and the Rolling Method is used for data prediction.

The forecast method in this research is described, as follows.

Moving Average Method

The weights of all the elements of the moving average are all the same, and the equation is, as follows:

$$F_t=(A_{t-1}+A_{t-2}+A_{t-3}+\ldots+A_{t-n})/n \quad (1)$$

F_t = Forecast value of next stage;

n = Number of stages in moving average;

A_{t-1} = The actual value of previous stage;

A_{t-2}, A_{t-3} and A_{t-n} represent the actual values of the first two stages, the first three stages, and the first n stages, respectively.

Exponential Smoothing

It is a kind of widely used short-term forecast method, and its equation is, as follows:

$$F_{t+1}=\alpha A_t+(1-\alpha)F_t \quad (2)$$

Where F_t represents the forecast value of the t^{th} stage, A_t represents the actual value of the t^{th} stage, F_{t+1} represents the forecast value of the $t+1^{th}$ stage, and α is the smoothing constant.

Linear and nonlinear Grey Forecasting Method

Grey modeling applies the accumulated generating operation (AGO) technique to reduce raw data randomization. The procedures for deriving linear and nonlinear grey forecasting models are derived below:

Step 1: Assume that the original series of data with *m* entries is:

$$X^{(0)}(1,m)=\left\{x^{(0)}(1),x^{(0)}(2),\ldots,x^{(0)}(k),\ldots,x^{(0)}(m)\right\}, \quad (3)$$

where raw matrix $X^{(0)}$ represents the non-negative original historical time series data.

Step 2: Construct $X^{(1)}$ using a one-time accumulated generation operation (1-AGO), namely

$$X^{(1)}(1,m)=\left\{x^{(1)}(1),x^{(1)}(2),\ldots,x^{(1)}(k),\ldots,x^{(1)}(m)\right\}, \quad (4)$$

where

$$x^{(1)}(k)=\sum_{i=1}^{k}x^{(0)}(i),\ k=1,2,\ldots,m. \quad (5)$$

Step 3: 1-AGO yields a monotonically increasing sequence similar to the solution curve of the first order linear differential equation. Therefore, the solution curve of the following differential equation approximates the 1-AGO data.

$$\frac{d\hat{x}^{(1)}}{dt}+a\hat{x}^{(1)}=b, \quad (6)$$

where ^ represents the Grey predicted value, and a and b are model parameters. Moreover, $\hat{x}^{(1)}(1)=x^{(0)}(1)$ is the corresponding initial condition.

Step 4: Model parameters a and b can be calculated by discretization of Eq. (4)

$$\frac{d\hat{x}^{(1)}}{dt}=\lim_{\Delta t\to 0}\frac{\hat{x}^{(1)}(t+\Delta t)-\hat{x}^{(1)}(t)}{\Delta t}. \quad (7)$$

let $\Delta t\to 1$, in which case 1-AGO approximates the forecast value,

$$\frac{d\hat{x}^{(1)}}{dt}\cong x^{(1)}(k+1)-x^{(1)}(k)=x^{(0)}(k+1), \; k=1,2,3, \quad (8)$$

$X^{(1)}$, the background value is defined as

$$\hat{x}^{(1)}(t)\cong px^{(1)}(k)+(1-p)x^{(1)}(k+1)=z^{(1)}(k+1), \; k=1,2,3,\ldots. \quad (9)$$

where p is in the range 0-1, and traditionally equals 0.5, in the original model. Moreover, the source model can be obtained, as follows:

$$x^{(0)}(k)+az^{(1)}(k)=b, \; k=2,3,4,\ldots\ldots \quad (10)$$

From Eq. (8), using the least square method, model parameters a and b become

$$\begin{bmatrix} a \\ b \end{bmatrix}=(B^TB)^{-1}B^TY_N, \quad (11)$$

where B and Y_N are defined, as follows:

$$B=\begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \vdots & \vdots \\ -z^{(1)}(m) & 1 \end{bmatrix}, \; Y_N=\begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(m) \end{bmatrix}, \quad (12)$$

Step 5: Solve Eq. (6) together with the initial condition, and the particular solution is

$$\hat{x}^{(1)}(k+1)=\left(x^{(0)}(1)-\frac{b}{a}\right)e^{-ak}+\frac{b}{a}, \; k=2,3,4,, \quad (13)$$

Consequently, the desired prediction output at step k can be estimated using the inverse accumulated generating operation (IAGO), as follows:

$$\hat{x}^{(0)}(k+1)=\left(1-e^{-a}\right)(x^{0}(1)-\frac{b}{a})e^{-ak}, \; k=1,2,3, \quad (14)$$

Step 6: Equation (6) is a linear differential equation and the only adjustable variable is p. Based on the elementary course in the ordinary differential equation, a differential equation similar to Eq. (6) is called the Bernoulli Equation, which is nonlinear and has the following form,

$$\frac{d\hat{x}^{(1)}}{dt}+a\hat{x}^{(1)}=b[\hat{x}^{(1)}]^n, \quad (15)$$

where n denotes any real number. This investigation terms this novel Grey differential equation as the Nonlinear Grey Bernoulli Equation (NGBM). From the above equation, when n=0, the solution reduces to Eq. (6): when n=2, the solution reduces to the Grey-Verhulst Equation.

Step 7: A discrete form of Eq. (15) is described as:

$$x^{(0)}(k)+az^{(1)}(k)=b[z^{(1)}(k)]^n, k=2,3,4,\ldots \quad (16)$$

Using the least square method, the above model parameters a and b become

$$\begin{bmatrix} a \\ b \end{bmatrix}=(B^TB)^{-1}B^TY_N, \quad (17)$$

where B and Y_N are defined, as follows:

$$B=\begin{bmatrix} -z^{(1)}(2) & [z^{(1)}(2)]^n \\ -z^{(1)}(3) & [z^{(1)}(3)]^n \\ \vdots & \vdots \\ -z^{(1)}(m) & [z^{(1)}(m)]^n \end{bmatrix}, \; Y_N=\begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(m) \end{bmatrix}, \quad (18)$$

Step 8: The corresponding particular solution of Eq. (15) is

$$\hat{x}^{(0)}(k+1)=\left[\left(x^{(0)}(1)^{(1-n)}-\frac{b}{a}\right)e^{-a(1-n)k}+\frac{b}{a}\right]^{1/(1-n)},$$
$$n\neq 1,\ k=1,2,3,\ldots\ldots, \quad (19)$$

For NGBM, p is traditionally set to 0.5, and the power n is used as the adjustable parameter.

Empirical Results and Analysis

Discussion and Analysis of Data

1. Monthly Concentration Change.

Figure 3 shows that the average concentration in winter (January-February and November-December) is higher than that in other months, the average concentration in June is the lowest, the monthly average value of 5 months in one year exceeds the daily average targeted value of 35 μg/m^3, the average concentration in summer is lower, and that in winter is higher.

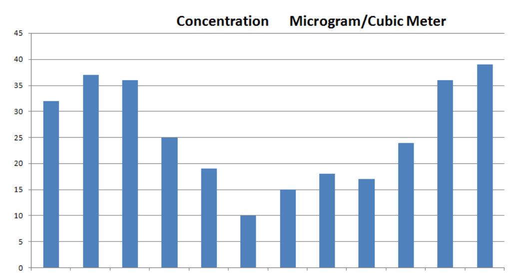

Figure 3. Monthly Average of $PM_{2.5}$
Source: https://taqm.epa.gov.tw/taqm/tw/YearlyDataDownload.aspx

2. Monthly Daily Average.

The monthly average $PM_{2.5}$ concentration trend has obvious seasonal changes: the concentration value in winter is higher, the highest daily average in November is 73μg/m^3, the lowest daily average is 7μg/m^3, and the difference is very large; the volatility of the daily average value in fall and winter is large, the concentration difference of the highest daily average and the lowest daily average in summer is about 20μg/m^3, which has small difference, and the common concentration value has lower trend.

3. The Number of Days of Daily Average Exceeding the Standard in each Month.

Figure 4 shows that the daily average concentration in fall and winter exceeds the PM2.5 air quality standard of the Environmental Protection Administration, that is, the number of days when 24-hour average targeted value is set as 35μg/m^3 is up to 21 days, while the number of days in summer when daily average exceeds the standard is 0, indicating that the Nantzu District has serious air pollution during fall and winter.

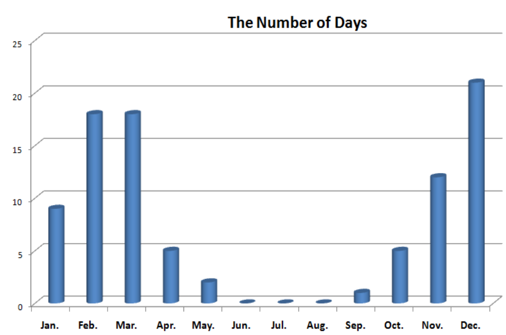

Figure 4. The Number of Days of $PM_{2.5}$ Concentration Exceeding the Standard in each Month
Source: https://taqm.epa.gov.tw/taqm/tw/YearlyDataDownload.aspx

4. Hourly Concentration Change in Four Seasons.

As shown in Figure 5, the lowest hourly concentration falls between 5 and 6 o 'clock every day and the concentration rises after 8 to 9 o 'clock in the morning. After noon, the concentration drops first, and then, rises again. The concentration falls to the lowest at 15 o 'clock in the afternoon in winter, and the concentration gradually rises between 16-17 o 'clock in the afternoon in spring, summer, and fall.

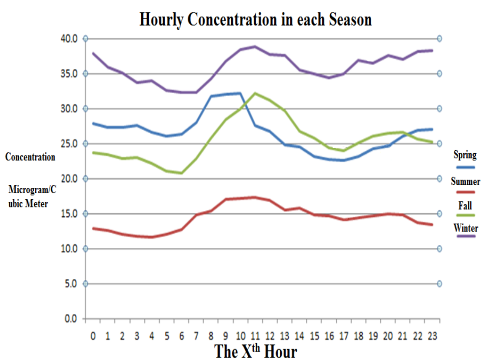

Figure 5 Broken Line Chart of Hourly Concentration Change in each Season
Source: https://taqm.epa.gov.tw/taqm/tw/YearlyDataDownload.aspx

$PM_{2.5}$ concentration has the characteristics of obvious seasonal changes; influenced by the emissions of pollution sources in different seasons, precipitation, wind speed, and other atmospheric diffusion conditions, the PM2.5 concentration has the trend of being higher in fall and winter, and lower in summer. The highest value of monthly concentration appears in November (fall and winter), while the lowest value appears in July and August (summer). As seen from the entire year: the concentration in winter is relatively higher than that in summer, and the hourly concentration in the evening is relatively higher than that in daytime. It rains more in summer and there are more typhoons in Taiwan, which is conducive to the spread and removal of PM2.5, and is possibly the reason for the lowest PM2.5 concentration in summer. Compared with rainfall in summer, the southern areas have dry air in winter, which does not favor the formation of precipitation, thus, it has short duration, its scouring effect on pollutants in the air is not obvious, and with the pollutants in the northeast monsoon, these are all the factors possibly leading to higher PM2.5 concentration.

The Result of Forecast

The accuracy of forecasting is related to the quality of management decisions. Short-term forecasting is relatively more accurate than long-term forecasting, thus, the requirement for accuracy is relatively higher. This research used Mean Absolute Percentage Error (MAPE) to compare the accuracy of each forecasting. When the MAPE value is smaller, it represents that the forecasting effect is better.

Table 1. Evaluation Criteria of MAPE Lewis (1982)

MAPE	Interpretation
<10%	Highly accurate forecasting
10%~20%	Good forecasting
20%~50%	Reasonable forecasting
>50%	Inaccurate forecasting

Moving Average Method

This research collected the daily average $PM_{2.5}$ concentration values of 12 months, from January 2016 to December 2016, as training data, the daily average of each month was forecast with the Moving Average Method in the probation period of 2-9, and Mean Absolute Percentage Error (MAPE) was calculated in accordance with the corresponding stage, as shown in Table 2. The MAPE values with shorter stages have better performance, the model with 2 stages has the best performance, thus, AP=2 is selected for forecasting if the Moving Average Method is used to forecast the daily average.

Table 2. MAPE Value Table Corresponding to AP=2~9 from January to December

Jan.	AP	2	3	4	5	6	7	8	9
	MAPE	48%	40%	36%	*33%	*33%	34%	34%	36%
Feb.	AP	2	3	4	5	6	7	8	9
	MAPE	*32%	37%	44%	51%	56%	59%	62%	64%
Mar.	AP	2	3	4	5	6	7	8	9
	MAPE	*22%	*22%	25%	25%	27%	28%	27%	26%
Apr.	AP	2	3	4	5	6	7	8	9
	MAPE	*29%	31%	*29%	32%	33%	31%	30%	30%
Jun.	AP	2	3	4	5	6	7	8	9
	MAPE	43%	*42%	*42%	46%	46%	51%	54%	59%
May.	AP	2	3	4	5	6	7	8	9
	MAPE	29%	*28%	*28%	*28%	29%	*28%	29%	29%
Jul.	AP	2	3	4	5	6	7	8	9
	MAPE	22%	20%	21%	19%	19%	17%	16%	*15%
Aug.	AP	2	3	4	5	6	7	8	9
	MAPE	*20%	21%	23%	24%	25%	27%	28%	29%
Sep.	AP	2	3	4	5	6	7	8	9
	MAPE	*34%	*34%	*34%	38%	41%	40%	44%	44%
Oct.	AP	2	3	4	5	6	7	8	9
	MAPE	*35%	40%	42%	44%	45%	45%	37%	*35%
Nov.	AP	2	3	4	5	6	7	8	9
	MAPE	*32%	34%	35%	39%	44%	50%	55%	60%
Dec.	AP	2	3	4	5	6	7	8	9
	MAPE	*22%	25%	24%	25%	23%	23%	24%	24%
*MAPE of that month is smallest						(Detailed forecast values are shown in Appendix)			

Exponential Smoothing

The daily average value in each month is forecast with the α value of 0.1-0.9, then, Mean Absolute Percentage Error (MAPE) was calculated according to the corresponding α. As shown in Table 3, the results show that a total of 7 MAPE values has better performance when α=0.8. Therefore, if Exponential Smoothing is used to construct the model, the daily average concentration shall be forecast with the use of α=0.8.

Table 3 MAPE Value Corresponding to α=0.1~0.9 from January to December

Jan.	a	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
	MAPE	59%	49%	46%	43%	42%	41%	40%	41%	41%
Feb.	a	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
	MAPE	41%	40%	38%	35%	32%	30%	29%	27%	27%
Mar.	a	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
	MAPE	31%	26%	23%	23%	22%	23%	23%	24%	25%
Apr.	a	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
	MAPE	61%	40%	34%	31%	29%	29%	29%	29%	30%
May.	a	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
	MAPE	123%	82%	64%	54%	50%	47%	44%	43%	44%
Jun.	a	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
	MAPE	26%	25%	25%	25%	26%	26%	26%	25%	25%
Jul.	a	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
	MAPE	20%	20%	21%	21%	21%	21%	21%	21%	22%
Aug.	a	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
	MAPE	26%	24%	23%	22%	21%	20%	20%	20%	20%
Sep.	a	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
	MAPE	62%	53%	45%	40%	38%	36%	36%	35%	35%
Oct.	a	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
	MAPE	33%	35%	35%	35%	33%	31%	30%	29%	29%
Nov.	a	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
	MAPE	42%	40%	35%	32%	31%	30%	30%	31%	32%
Dec.	a	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
	MAPE	21%	23%	23%	23%	23%	23%	23%	23%	23%
*MAPE of that month is smallest							(Detailed forecast values are shown in Appendix)			

Grey Forecasting Method

This research used the linear and non-linear equations of the Grey Forecasting Method to forecast, and respectively used 4Data, 5Data, and 6

Data rolling method to construct the model, (Table 4), and the results show that model construction with 4data is the best, as compared with other models. The nonlinear rolling of residual values in 3 days is 3.4%, nonlinear rolling in 1 day is 3.28%, linear rolling in 5 days is 6.3%, linear rolling in 1 day is 10.66%, and the linear and nonlinear comparison results show that nonlinear accuracy is better; therefore, the result is that the model construction with fewer observations and nonlinear pattern has the best performance. In terms of forecasting, although the model constructed with residual error values is very good, the forecast result is very unsatisfactory (Table 5). The possible reason is that the change of concentration value of $PM_{2.5}$ is too large. According to the results of literature discussion, the source composition of $PM_{2.5}$ is complex, which is difficult to effectively control, thus, the forecasting result is not ideal.

Table 4. Model Construction Residual Error Table

Model Construction Residual Error	6data	5data	4data
Nonlinear, roll in three days	13.4%	5.80%	3.40%
Nonlinear, roll in one day	11.86%	8.36%	3.28%
Linear, roll in five days	13.70%	13.90%	6.30%
Linear, roll in one day	18.93%	14.58%	10.66%

Table 5. Forecast Residual Error Table.

Forecast Residual Error	6data	5data	4data
Nonlinear, roll in three days	59.3%	62.40%	60.10%
Nonlinear, roll in one day	81.00%	80.00%	78.00%
Linear, roll in five days	153.50%	67.20%	65.50%
Linear, roll in one day	112.00%	107.00%	126.00%

Comparison of Forecast Methods in this Research

This research compared three forecasting methods (Table 6), which used AP value, stages, and models with good performance, respectively, and the results show that Exponential Smoothing

Table 6. Comparison of Forecasting Methods in this Research

Date	Value of PM2.5	Exponential Smoothing Method		Moving Average Method		Grey Forecasting	
		α =0.8	Error(%)	AP=2	Error(%)	4Data	Error(%)
2016/2/1	25						
2016/2/2	23	25	8.7%				
2016/2/3	33	23.4	29.1%	24	27.3%		
2016/2/4	39	31.08	20.3%	28	28.2%		
2016/2/5	27	37.42	38.6%	36	33.3%	50.5	87%
2016/2/6	65	29.08	55.3%	33	49.2%	64.6	1%
2016/2/7	57	57.82	1.4%	46	19.3%	82.6	45%
2016/2/8	38	57.16	50.4%	61	60.5%	105.7	178%
2016/2/9	30	41.83	39.4%	47.5	58.3%	15.9	47%
2016/2/10	23	32.37	40.7%	34	47.8%	10.4	55%
2016/2/11	22	24.87	13.1%	26.5	20.5%	6.8	69%
2016/2/12	10	22.57	125.8%	22.5	125.0%	4.4	56%
2016/2/13	10	12.51	25.2%	16	60.0%	9.4	6%
2016/2/14	13	10.5	19.2%	10	23.1%	6.8	48%
2016/2/15	31	12.5	59.7%	11.5	62.9%	5.0	84%
2016/2/16	44	27.3	38.0%	22	50.0%	3.6	92%
2016/2/17	48	40.66	15.3%	37.5	21.9%	72.8	52%
2016/2/18	47	46.53	1.0%	46	2.1%	120.4	156%
2016/2/19	56	46.91	16.2%	47.5	15.2%	198.9	255%
2016/2/20	40	54.18	35.5%	51.5	28.8%	328.7	722%
2016/2/21	53	42.84	19.2%	48	9.4%	41.6	22%
2016/2/22	46	50.97	10.8%	46.5	1.1%	38.9	15%
2016/2/23	50	46.99	6.0%	49.5	1.0%	36.3	27%
2016/2/24	31	49.4	59.4%	48	54.8%	34.0	10%
2016/2/25	41	34.68	15.4%	40.5	1.2%	30.4	26%
2016/2/26	40	39.74	0.7%	36	10.0%	25.8	35%
2016/2/27	37	39.95	8.0%	40.5	9.5%	22.0	41%
2016/2/28	42	37.59	10.5%	38.5	8.3%	18.7	56%
2016/2/29	48	41.12	14.3%	39.5	17.7%	41.8	13%
MAPE			27.4%		31.4%		88%

has good performance. Although the forecasting ability of the residual value of forecasting results > 20% is only reasonable, its forecasting results are still good after being compared with other forecasting methods.

Conclusion

In order to effectively forecast the change trend of $PM_{2.5}$ concentrations, three methods, including the Moving Average Method, Exponential Smoothing Method, and Grey Forecasting Method, were used in this research. The research results show that the forecasting effect of Exponential Smoothing (α=0.8) is the best, followed by the Moving Average Method and Grey Forecasting Method. The reason is the daily change of $PM_{2.5}$ concentration is highly nonlinear, thus, forecasting accuracy will drop with the use of linear or nonlinear grey forecasting model due to the changing area rate of the fitting curve. While forecasting methods that apply the average concept fail to pursue high accuracy forecasting of a single point, they consider the overall forecasting accuracy, thus, showing the advantages of the Exponential Smoothing and Moving Average Methods.

Acknowledgements

This research is completed with funds provided by MOST 106-2221-E-214-042, as planned by the Ministry of Science and Technology. We appreciate the support very much.

References

Air Protection Department, Environmental Protection Administration, Executive Yuan (2015), https://enews.epa.gov.tw/enews/fact_Newsdetail.asp?InputTime=1040428103015.

Environmental Protection Administration, Executive Yuan, https://taqm.epa.gov.tw/taqm/tw/YearlyDataDownload.aspx

Weng, S.P., Kuo, N.W., Lu, P.W. (2013), The Synoptic Environmental Settings of PM2.5 Contamination Events in the Kaohsiung-Pingtung Areas, Atmospheric Sciences, 41(1), 43-64.

Tsai, H. T., Yang, K. H., Huang, H. F. (2017), 空 New Deed of Prevention and Treatment of Air Pollution, Public Governance Quarterly, 5(3), 108-113.

Fruin, S. Westerdahl, D. Sax, T. Sioutas, C. Fine, P., (2008),Measurements and predictors of on-road ultrafine particle concentrations and associated pollutants in Los Angeles. Atmos Environ. Vol. 42(2), 207-219.

Jacobson, M. Z., (2002), Control of fossil-fuel particulate black carbon and organic matter, possibly the most effective method of slowing global warming. J Geophys Res. 107 (D19).

Kampa, M. and E. Castanas (2008), ”Human Health Effects of Air Pollution,” Environmental Pollution, Vol. 151, 362–367.

Kulmala, M.; Vehkamäki, H.; Petäjä, T.; Dal Maso, M.; Lauri, A.; Kerminen, V.-M.; Birmili, W.; McMurry, P. H.,(2004), Formation and growth rates of ultrafine atmospheric particles: a review of observations. J Aerosol Sci. Vol. 35 (2), 143-176.

Lewis, E. B. (1982),Control of body segment differentiation in Drosophila by the bithorax gene complex, Embryonic Development, Part A: Genetics Aspects, Edited by Burger, M. M. and R. Weber. Alan R. Liss, New York, 269-288.

Pérez, N.; Pey, J.; Cusack, M.; Reche, C.; Querol, X.; Alastyey, A; Viana, M.,(2010),Variability of particle number,black carbon, and PM10, PM2.5, and PM1 levels and speciation: influence of road traffic emissions on urban air quality. Aerosol Sci Tech. Vol. 44(7), 487-499.

Salako, G. O.,(2012),Exploring the Variation between EC and BC in a Variety of Locations. Aerosol Air Qual Res.

Samet, J. M., Dominici, F., Curriero, F., Coursac, I., Zeger, S. L., (2000), “Fine particulate air pollution and mortality in 20 U.S. cities: 1987-1994.” New England Journal of Medicine, Vol. 343, 1742-1757.

Seinfeld, J. H,; Pandis, S. N., From air pollution to climate change. Atmospheric hemistry and physics. Wiley-Interscience, New York. 1998, 700-765.

Shah, J. J. and Rau, J.A.,(1990),Carbonaceous Species Methods Comparison Study: Interlaboratory Round Robin Interpretation of Results, Final Report to Research Division, Air Resources Board. California. A832-154, 77.

Woodruff, T. J., Parker, J. D., & Schoendorf, K. C. (2006). Fine particulate matter (PM2.5) air pollution and selected causes of postneonatal infant mortality in California. Environmental Health Perspectives,Vol. 114(5), 786.