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Research on Air Quality in Response to Meteorological Factors Based on the Informer Model

Xiaoqing Tian ^{1,2} , Chaoqun Zhang ^{1,2}, Huan Liu ³, Baofeng Zhang ⁴, Cheng Lu ⁵, Pengfei Jiao ³ and Songkai Ren ^{1,2,*}

¹ International Co-Operation Platform of Intelligent Ocean Equipments Technology of Zhejiang Province, Hangzhou Dianzi University, Hangzhou 310052, China; tianxiaoqing@hdu.edu.cn (X.T.); zhangchaoqun@hdu.edu.cn (C.Z.)

² School of Mechanical Engineering, Hangzhou Dianzi University, Hangzhou 310018, China

³ School of Cyberspace Security, Hangzhou Dianzi University, Hangzhou 310018, China; huanliu@hdu.edu.cn (H.L.); pjiao@hdu.edu.cn (P.J.)

⁴ Hangzhou Eco-Environment Monitoring Center, Hangzhou 310012, China; im.bfzhang@gmail.com

⁵ Zhejiang Institute of Hydraulics & Estuary, Hangzhou 310020, China; yjy@zjwater.gov.cn

* Correspondence: rensongkai@hdu.edu.cn

Abstract: The quality of the air exerts considerable effects on human health, and meteorological factors affect air quality. The relationships between meteorological factors and air quality parameters are complex dependency correlations. This article is based on the air quality monitoring data and meteorological monitoring data obtained from a monitoring station in Binjiang District, Hangzhou City, China, spanning from 01:00 on 14 April 2021 to 23:00 on 31 December 2021. The Informer model was used to explore the air quality parameters' response to meteorological factors. By analyzing 12 different kinds of 2-Minute Average Wind Speed (2-MAWSP), 10-Minute Average Wind Speed (10-MAWSP), and Maximum Wind Speed (MXSPD); 16 different kinds of Hourly Precipitation (HP) and Air Temperature (AT); 11 different kinds of Relative Humidity (RH); and 8 different kinds of Station Pressure (STP), the following results were obtained: (1) The influence of wind speed on various air quality parameters is multifaceted and lacks a standardized form, potentially influenced by factors like wind direction and geographical location. One clear effect of wind speed is evident in the levels of particulate matter 10 (with an aerodynamic diameter smaller than 10 μm , PM_{10}), as the values of this parameter first decrease and then increase with increasing wind speed. (2) HP has an evident reducing effect on most air quality parameters, including particulate matter (including $\text{PM}_{2.5}$ and PM_{10}), ozone (O_3), sulfur dioxide (SO_2), and nitrogen dioxide (NO_2), as well as nitrogen oxides (NO_x). (3) The increase in AT has a clear reducing effect on the concentration of NO_2 , while the trend for the concentrations of PM_{10} and NO_x is one of initial decrease followed by a gradual rise. (4) RH only reduces the concentrations of SO_2 and PM_{10} . (5) With the rise in STP, the concentrations of most air quality parameters generally rise as well, except for the decrease in NO_x concentration. This can give some indications and assistance to meteorological and environmental departments for improving air quality. This model can be used for a performance analysis and the forecasting of multi-parameter non-correlated systems.

Keywords: air quality parameters; meteorological factors; response; informer model



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1. Introduction

Excellent air quality is beneficial for staying healthy; thus, more and more researchers are focused on air quality improvements. For instance, the Australian bushfires in 2019 [1] and the wildfires in Brazil [2] released a range of pollutants into the air, resulting in extremely poor air quality conditions in the relevant areas. These pollutants did not dissipate immediately but, instead, dispersed and diffused throughout the atmosphere [3,4], presenting an ongoing threat to human health. Meanwhile, the air quality is affected by

meteorological factors. Therefore, numerous experts have conducted a wide range of analyses to figure out the response of the air quality parameters to the meteorological factors. However, their highly nonlinear relationships within a time series pose significant challenges to such studies.

Numerous researchers have investigated the nonlinear relationships between air quality parameters and meteorological factors. Li et al. [5] determined the correlation between different meteorological factors and the API by employing an STL technique in conjunction with a Wavelet Analysis. Their findings revealed an inverse relationship between temperature, RH, precipitation, and wind speed, and the API. Conversely, both the day–night temperature difference and atmospheric pressure exhibited a direct correlation with the API throughout the yearly cycle. Chen et al. [6] employed the CCM method to evaluate the causal impact of specific meteorological elements on PM_{2.5} levels. The results showed that meteorology has a significant impact on PM_{2.5} concentration, and the higher the PM_{2.5} concentration, the stronger the influence of the meteorological factors on PM_{2.5} concentration. Palmeira et al. [7] evaluated the long-term dependencies between three atmospheric pollutants and four climate variables, as well as the cross-correlation between these dependencies and climate variables, using a DFA and a ρ DCCA, respectively. The findings indicate that there is a mutual correlation between atmospheric pollution and climate variables, especially a strong association between O₃ and wind, as well as temperature, alongside a pronounced adverse correlation with humidity. Hu et al. [8] explored the response between air quality parameters and meteorological factors by calculating the Pearson correlation coefficient; these findings indicated that atmospheric pressure, RH, and temperature significantly influenced the air quality parameters. Li et al. [9] used the Spearman correlation coefficient to explore the responses between the concentration of airborne particulate matter and the meteorological factors, indicating that in most regions, the concentration of particulate matter demonstrated a negative correlation with cumulative precipitation.

Although classical analysis methods have provided valuable insights into the response between air quality parameters and meteorological factors, they fall short in capturing the specific nonlinear responses between these variables. Furthermore, another challenge is the complex interdependency between meteorological elements and air quality indicators.

Recently, AI models have demonstrated significant advantages in exploring the responses within complex nonlinear data. It has attracted a large number of scholars to apply AI models to air quality-related research [10–17]. These studies focused on the field of air quality prediction and treatments. An example is the research into models that forecast PM_{2.5} concentrations. Various external factors often influence the level of PM_{2.5} concentration, exhibiting intricate spatiotemporal reliance [18]. The application of statistical models, models like the ARMA [19] and the ARIMA [20,21], to predict PM_{2.5} concentrations is often susceptible to bias in the face of complex nonlinear relations. Highly adaptable and robust, artificial neural networks demonstrate remarkable flexibility and durability because information is distributed and stored in the neurons of the network. When addressing prediction challenges, particularly those involving RNNs, their performance is outstanding. Both RNNs and LSTM are frequently employed in the processing and forecasting of pollutant concentrations over different time spans [22]. Kristiani et al. [23] utilized both RNN and LSTM models for forecasting PM_{2.5} concentrations within eight hours, with good prediction results. However, these models have limitations in long sequence prediction problems because of the gradient problem associated with RNNs and the inability of LSTMs to perform parallel computations [24]. In order to improve the above models, some researchers have introduced attention mechanisms into their research work [25]. Important contextual information can be extracted through the utilization of this mechanism, but its inherent characteristics limit its long-term predictive ability.

Compare to the above-mentioned models, the Transformer model can eliminate the reliance on sequential structure [26]. Its entire network structure is entirely composed of self-attention mechanisms, achieving high-performance parallel operations. The ability

to conduct parallel processing and extract temporal features from time series data is significantly improved by this model. Yu et al. [27] utilized the improved STT for forecasting PM_{2.5} concentrations in regions prone to wildfires, and the model shows a better ability for describing abrupt changes in PM_{2.5} concentrations than other time-series forecasting methods. However, it can be noted that the Transformer model has the inefficiency of input and output operations for long sequences, the complexity of self-attention quadratic computation, the large memory occupation of stacking layers, and the slow prediction speed of a step-by-step model. In view of the above problems of the traditional Transformer model, Zhou et al. [28] introduced innovative structures and mechanisms aimed at capturing non-smooth and long-term temporal dependencies. They subsequently proposed the Informer model, which significantly enhanced the efficiency and accuracy in processing long-series time-series data [29]. Lai et al. [30] used the improved EIDW-Informer model to predict PM_{2.5}, NO₂, and O₃ concentrations, and compared with LSTM, CNN-LSTM, and Attention LSTM models, the EIDW-Informer model has the best predictive performance.

Obtaining the specific response relations between air quality and meteorological factors in a certain area has potential application significance in reality. It can provide a specific reference for improving local air quality and can enrich the means to improve air quality. Extensive research has been conducted by scholars to explore various methods for air quality improvements. Guo et al. [31] employed a distributed lag nonlinear model to explore the relationship between rainfall and PM concentrations. Rainfall has a significant wash out effect on PM. Zhang et al. [32] and He et al. [33] investigated the interactions between meteorological parameters and air pollutants in several large Chinese cities, focusing on the physical mechanisms that drive the relationships between meteorological factors and air quality.

This study will use the Informer model to investigate the correlation between air quality parameters and meteorological factors. This paper is organized as follows: In Section 2, we introduce the model employed in this study. In Section 3, the effectiveness of this model is verified. In Section 4, we present the results of using the Informer model to obtain the response relationship between air quality parameters and meteorological factors. Finally, in Section 5, we will draw several conclusions from this study.

2. Methodology

The Informer model, based on the self-attention mechanism, is a supervised learning model that represents an advancement from the Transformer model [26,28]. The LSTF problems are significantly improved by the effective application of the Informer model. It addresses three major issues present in the Transformer model. First, the problem of inefficient input and output operations for long sequences is tackled by proposing a PSSA mechanism [34]. Second, a SAD mechanism has been suggested to address the problem of the self-attention quadratic computation being too complex and the stacking layer occupying a large amount of memory. Third, the problem of a slow prediction speed is addressed by the GSD method, which obtains prediction results in a single step [28].

As shown in Figure 1, the structure of the Informer model closely resembles that of the Transformer model, as both are supervised learning models based on the self-attention mechanism [35]. The entire model comprises two components: the encoder and the decoder.

The encoder component is specifically designed to capture the robust long-term dependencies from the long sequential inputs [35]. For LSTF problems, the predictive performance of the Informer model relies heavily on its capacity to capture long-term dependencies. It is worth noting that this capability is closely tied to how effectively the model uses global information [36,37], so a uniform input representation method has been developed. The encoder receives the input after the embedding operation. There exists a potential sparsity in the distribution of self-attention probabilities. In other words, only a few point product pairs make significant contributions to the primary attention, while the attention of the remaining point product pairs is nearly negligible. The PSSA effectively resolves the temporal complexity associated with self-attention dot product calculations.

From a multi-head viewpoint, the attention mechanism produces distinct sparse query-key pairs for each individual head. Thus, serious information loss is prevented. The feature map of the encoder has redundant combinations. To reduce complexity, SAD is used to prioritize superior features with dominant features. To enhance the robustness of SAD, a replica of the primary stack utilizing halved inputs is constructed. Finally, the outputs from every stack are connected to obtain the ultimate encoded representation obtained from the encoder.

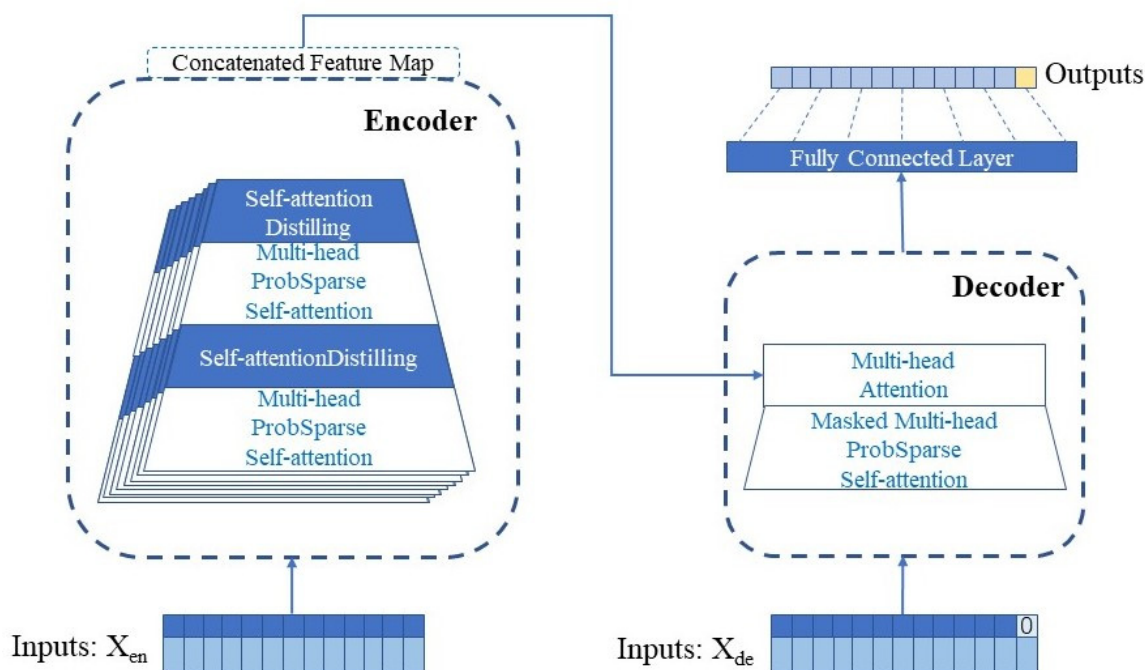


Figure 1. The architecture of the Informer model.

The decoder structure is stacked with MMHPSSA and “MHPSSA”. First, the decoder initially receives an extensive series of inputs and inserts a 0 at the predicted target position. Since the part of the information that the Informer model is trying to predict is supposed to be unknown, MMHPSSA is used in the first layer to mask the part of the input that is to be predicted. Then, PSSA is used to compute the output of the current layer based on a priori information. In the second layer, Multi-Head ProbSparse Self-Attention comes into play to grasp the relationships between the data in the input and generate predictions. Finally, an FCL is tasked with delivering the ultimate output. The Informer model’s inputs consist of long sequential data, which are processed through an embedding step followed by encoding to capture dependencies and features. The outputs include encoded representations optimized for downstream tasks and predictions generated by the decoder for forecasting applications.

3. Model Calibration

To evaluate the precision of the Informer model in predicting the nonlinear response relations between air quality parameters and meteorological factors, a real example involving a fire event is examined, and the time event is in local standard time.

At around 13:30 on 1 November 2021, a fire erupted in a factory building located on Yangcheng Road, Xiaoshan District, Hangzhou, Zhejiang. The fire was extinguished at around 16:00. However, the pollution event lasted about 33.5 h, ending at 23:00 on 2 November 2021. During this event, many air quality parameters (PM_{2.5}, PM₁₀, SO₂, and NO_x) reached peak values, affecting traffic and city life. Additionally, rain fell from 14:00 to 16:00 on 2 November 2021.

The data utilized to validate the accuracy of the Informer model were gathered from the Xiaoshan Air Quality Monitoring Station and the Xiaoshan National Meteorological Monitoring Station within a 12 h timeframe after the precipitation event. These data types are similar to the Binjiang District data used in Section 4. The results of model response testing on the model are shown in Figure 2. The simulated curve of $PM_{2.5}$ closely aligns with the measured curve. The MRE between the actual and predicted data is about 4.12%. The formula for MRE is shown in (1). Additionally, other air quality parameters, for instance, PM_{10} , SO_2 , and NO_x , are analyzed as well. As shown in Figure 2b–d, the MRE values for these pollutants are 4.33%, 5.55%, and 7.00%, respectively. Most importantly, the model captured the decreases in $PM_{2.5}$, PM_{10} , SO_2 , and NO_x concentrations caused by rainfall. This indicates that the model has reliable performance in capturing meteorological factors and responding to air pollution.

$$MRE = \frac{1}{n} \sum_{i=1}^n \left| \frac{m_i - \bar{p}_i}{m_i} \right| \quad (1)$$

where n represents the overall count of samples, p_i signifies the predicted value of the model at time i , and m_i indicates the measured value of the model at time i .

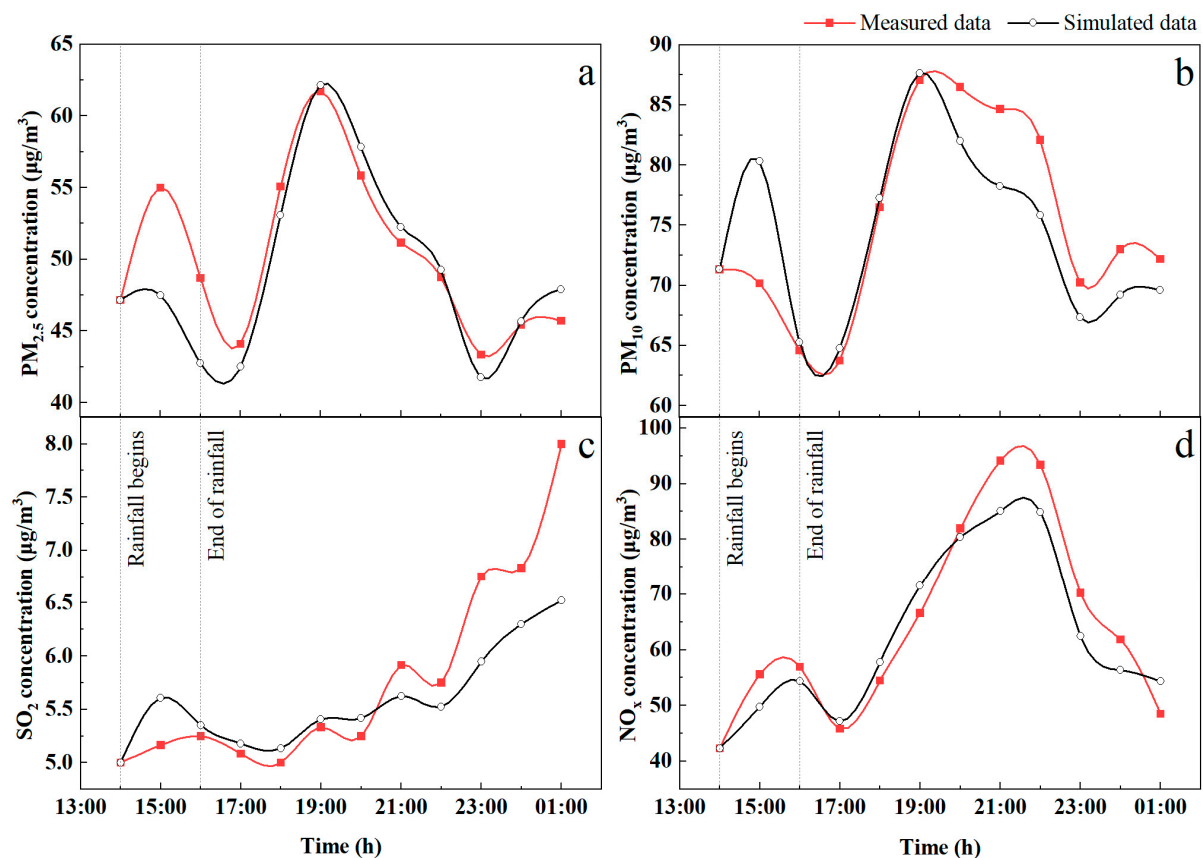


Figure 2. The fit of the Informer model prediction curves and the measurement curves after rainfall. The (a–d) correspond to the measured and predicted curves for $PM_{2.5}$, PM_{10} , SO_2 , and NO_x , and the red line means the predicted values, while the black line represents the measured values.

4. Numerical Example

4.1. Study Data

4.1.1. Data

This study aims to explore the response relation between air quality monitoring data and meteorological monitoring data through the Informer model. As illustrated in Figure 3, the data were obtained from the Air Quality Monitoring Station (Point A) and

the National Meteorological Monitoring Station (Point B), respectively. The straight-line distance between stations A and B is approximately 4.2 km. The air quality monitoring data mainly include eight air pollutant parameters, as shown in Table A1. The meteorological monitoring data include 21 parameters, as shown in Table A2. (All other abbreviations of nomenclatures that appear in this paper are listed in Table A3).



Figure 3. A diagrammatic representation of the study area (A: Binjiang Meteorological Monitoring Station, B: Binjiang Air Quality Monitoring Station).

From the air quality monitoring data, $PM_{2.5}$, PM_{10} , SO_2 , O_3 , NO , NO_2 , and NO_x are selected as the identifiers j , $j \in \{1, 2, 3, 4, 5, 6, 7\}$. From the meteorological monitoring data, 2-MAWSP, 10-MAWSP, MXSPD, HP, AT, RH, and STP are selected as the identifiers k , $k \in \{1, 2, 3, 4, 5, 6, 7\}$. The selected data period is from 01:00 on 14 April 2021 to 23:00 on 31 December 2021. It is worth remarking that the air quality monitoring data are averaged hourly values with a time interval of 1 h. In contrast, the meteorological monitoring data have a time interval of 1 min. To unify the time intervals of these two datasets, we calculated the hourly averages for the meteorological monitoring data. It is important to note that the values for 2-MAWSP and 10-MAWSP are directly recorded by the instruments. We performed a simple averaging process on these values to align them with the hourly interval, which does not substantively change the parameter types.

The data, which were employed in model training, were gathered through the pre-processing stage. The Pearson Correlation Analysis and GRA were simply applied to gain the correlations and dependencies among the different parameters in these data. The Pearson Correlation Analysis focuses on evaluating the linear relationship between two continuous variables, measuring the strength and direction of this relationship. It is mainly used to indirectly demonstrate the highly nonlinear characteristics of the data. On the other hand, GRA primarily reveals the complex dependencies among various types of data within air quality and meteorological monitoring datasets.

The Pearson Correlation Analysis [38] serves as a straightforward and applicable method for measuring the degree of linear correlation between variables. For instance, using $PM_{2.5}$ concentration data, we perform a Pearson Correlation Analysis with the seven meteorological factors of interest. The results are presented in Figure 4. According to Figure 4, with a sufficiently small p -value, the correlation coefficients r between the $PM_{2.5}$ concentration data and the other meteorological factors are negative and $r < 0.05$, except for STP. (Here is a note: in Figure 4, the p value between HP and O_3 reached 0.739, which is greater than the threshold of 0.05. At this point, describing the correlation between HP and

O₃ is beyond the capabilities of the Pearson Correlation Analysis.) It can be inferred that the response between the air quality parameters and meteorological factors is highly nonlinear.

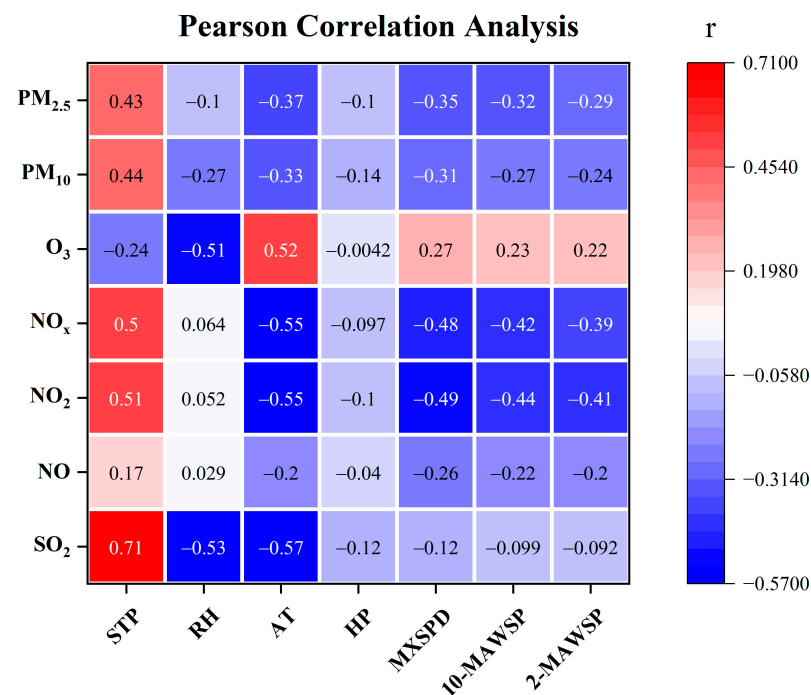


Figure 4. Heat map of the Pearson Correlation Analysis between air quality parameters and meteorological factors.

GRA [39] is another method for multi-factor statistical analysis. It characterizes the relative strength of a factor we are concerned about in a grey system that is influenced by other factors. We conducted a grey relational analysis on seven meteorological condition data and seven air pollutant concentration data, with the results shown in Figure 5. Taking PM_{2.5} as an example, with a distinguished coefficient of $\rho = 0.5$, it is evident that PM_{2.5} is not only closely related to meteorological factors but also has a strong connection with the concentrations of the other air quality parameters. The results of the GRA indicate that there is a complex dependency correlation between the meteorological factors and air quality parameters.

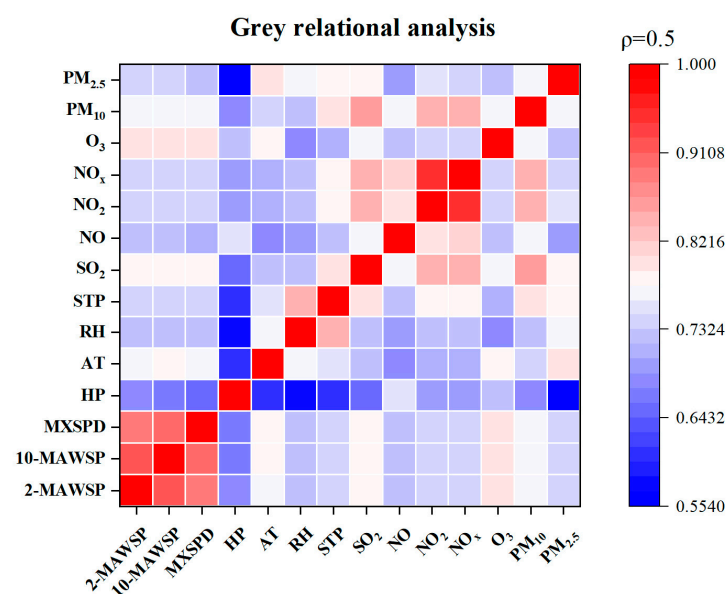


Figure 5. Heat map of a GRA between air quality parameters and meteorological factors.

4.1.2. Model Performance Evaluation Metrics

For the purpose of effectively assessing the training performance of the model, MAE and RMSE were employed as the measures of evaluation. The formulas for both are as follows:

$$MAE = \frac{1}{n} \sum_{i=1}^n |m_i - p_i| \quad (2)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (m_i - p_i)^2} \quad (3)$$

where n represents the overall count of samples, p_i signifies the predicted value of the model at time i , and m_i indicates the measured value of the model at time i .

4.2. Research Process

The procedure is illustrated in Figure 6: Firstly, the obtained raw data were pre-processed to obtain the pre-processed data. Next, the pre-processed data were divided into different datasets and embedded. During this process, the data for response testing were extracted from the testing set and made into testing samples. Then, the Informer model was trained using the embedded data. Finally, the test samples were employed to test the response of the trained Informer model to obtain the final result.

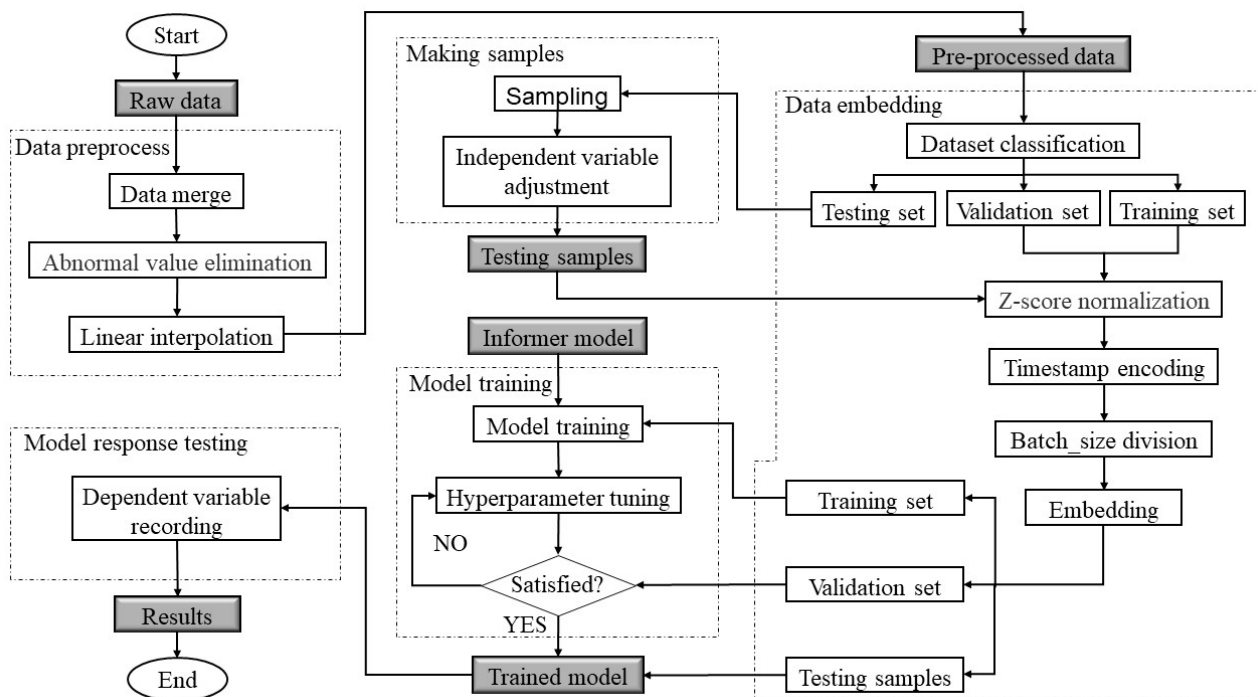


Figure 6. A flowchart of the Informer model.

4.2.1. Data Preprocessing

Firstly, the air quality observation data and meteorological observation data were merged according to the time dimension, with the unified time interval being hourly and the specific value taken as the hourly average. Secondly, the boxplot method was used to eliminate outliers in the data. Finally, a linear interpolation was performed on the missing data, resulting in preprocessed data for training that included 29 dimensions and a total of 6287 entries.

4.2.2. Data Embedding

The preprocessed data were divided into training, validation, and test sets in a ratio of 7:1:2. Since different types of data have different scales, it may cause the training data to

be distributed into the saturated region of the activation function, negatively affecting the model's precision and rate of convergence. Therefore, the z-score normalization is used in this study to eliminate unit effects [40]. Then, the data exhibit a normal distribution, having a mean of 0 and a variance of 1. The formula is as follows:

$$Z = \frac{x - \mu}{\sigma} \quad (4)$$

where x is the original value, μ is the mean of the data, and σ represents the standard deviation of the data.

After z-score normalization, the time column data in the preprocessed data were firstly converted into a unified time format. Then, the time data column was time-stamp-encoded. The specific operation of time-stamped encoding is to encode the time column data into the corresponding hour, week, month, and year of the current time. Then, the encoded time column data were mapped to the value range of $[-0.5, 0.5]$. After the above operation, the data were divided into batches, where the batch size was 32. Then, the data were embedded. The embedding operation has three parts: scalar projection, local timestamps (relative position), and global timestamps (hour, week, month, and year). After the final step of embedding, the data can be input into the model directly.

4.2.3. Model Training

Before model training, first, the Informer model was built. The prediction output parameters of the Informer model were then set to $PM_{2.5}$, PM_{10} , O_3 , SO_2 , NO , NO_2 , and NO_x . The embedded training set data were input in batches of the same size into the built Informer model for training. Remarkably, the model inputs used to predict $PM_{2.5}$, PM_{10} , O_3 , SO_2 , NO , NO_2 , and NO_x were the same, utilizing the same dataset. During training, the model output corresponding prediction values ($PM_{2.5}$, PM_{10} , O_3 , SO_2 , NO , NO_2 , and NO_x) based on the input data. The prediction values from the measured values were subtracted to obtain an error value. The model backpropagated this error value to update the parameters in the model, making the model evolve towards a smaller prediction error. Then, the model input the next batch of data, repeating the process from model prediction to model parameter update. This process was repeated until the training set data were traversed once. Then, the validation set data were used to fine-tune the model hyperparameters until the learning rate did not change for 10 consecutive times. The trained model was then saved. The specific hyperparameters used for the Informer model training are shown in Table 1.

Table 1. Model hyperparameter settings.

Hyperparameters	Value	Hyperparameters	Value
Time encoding length	Hour	Number of heads of attention	8
Encoder step size	12	Encoder stacking	3, 2, 1
Decoder step size	12	Regularization settings	0.05
Prediction step size	1	Activation function	gelu
Encoding dimension	29	batch size	32
Decoding dimensions	29	Initial learning rate	0.0001
Output dimensions	1	loss function	mse

4.2.4. Model Response Testing

After the model was trained, it was tested for the response stored in the model between the air quality parameters and meteorological factors. The previously trained model was called, and the types of air quality parameters to be predicted were set, marked as j .

A segment of the test set data with a time step length of 13 was selected as the test sample. The seven meteorological factors 2-MAWSP, 10-MAWSP, MXSPD, HP, AT, RH, and STP were sequentially used as independent variables X^{j+k} , $X^{j+k} = \{x_i^{j+k}\} (i \in N)$, with the meteorological factors marked as k , $k \in \{1, 2, 3, 4, 5, 6, 7\}$. The value of the independent

variable x_{12}^{j+k} at the 12th time step in the test sample was altered according to a certain pattern, and then, the test sample with the modified independent variable was input into the trained model. The model's predicted value of the dependent variable y_{13}^{j+k} at the 13th time step, based on the data from time steps 1–12, was observed and recorded. This provided the response curve of the dependent variable Y^{j+k} with respect to the independent variable X^{j+k} , which is the model response curve of air pollutant concentration with respect to meteorological factors.

Now, taking the response curve study of PM_{2.5} concentration with respect to HP as an example, the testing process is explained. The test sample was input into the PM_{2.5} concentration prediction model (the test sample is shown in Table 2). The actual value of PM_{2.5} at the 13th time step was 43.5. Without altering the test sample data, the model predicted a PM_{2.5} value of 41.25 for the 13th step. Then, the HP value at the 12th time step in the test sample was changed to 10, and the model was run again for prediction, resulting in a PM_{2.5} value of 40.5. Following the above steps, the HP value at the 12th step was changed from 0 to 600 in succession, and the final model response curve was obtained.

Table 2. Data samples for testing.

Time Step	Maximum Instantaneous Wind Speed	...	HP	...	PM _{2.5}
1	20		0		40.67
2	16		2		35.25
⋮	...	...	⋮	...	⋮
12	43		0		48.02
13	60		0		43.5

4.3. Results

4.3.1. The Predictive Performance of the Model

As shown in Figure 7, the curve represents the predictive performance of the model trained in this research on the prediction set. Combining Figure 7 and Table 3, it is apparent that the forecast accuracy for SO₂ surpasses all others, with the smallest MAE and RMSE among all the air quality parameters predicted by the Informer model. The forecasting performance for O₃ is the worst, with its MAE and RMSE reaching 13.76% and 16.50%, respectively, the highest among the seven pollutants predicted. As seen in Figure 7c, the high-frequency fluctuations in the O₃ concentration curve resulted in a slightly higher prediction error compared to the other counterparts, but the error remained within an acceptable range.

Table 3. Training effects of the model.

Pollutants Predicted by the Model	MAE	RMSE
PM _{2.5}	7.70%	9.46%
PM ₁₀	10.32%	12.99%
O ₃	13.76%	16.50%
SO ₂	0.95%	1.16%
NO	2.20%	2.67%
NO ₂	7.16%	9.06%
NO _x	8.50%	10.55%

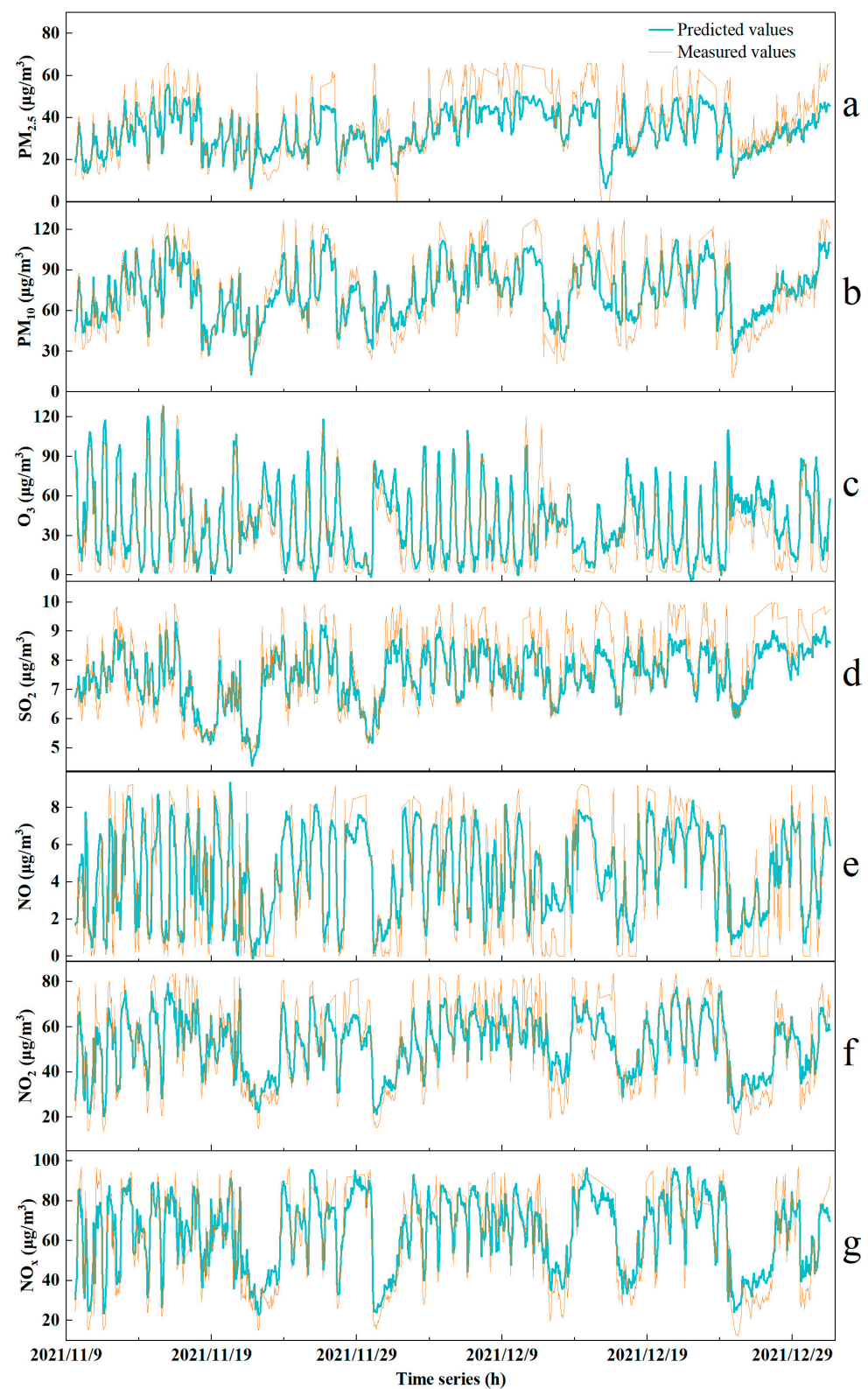


Figure 7. Prediction curves of the Informer model for $PM_{2.5}$, PM_{10} , O_3 , SO_2 , NO , NO_2 , and NO_x are shown in (a–g) in sequence, and the green line means the predicted value while the orange line means the measured value.

4.3.2. Prediction of Air Quality Parameters' Response to Different Meteorological Factors

Figures 8–14 depict the response between the seven air quality parameters and seven meteorological factors, as modeled by the Informer model.

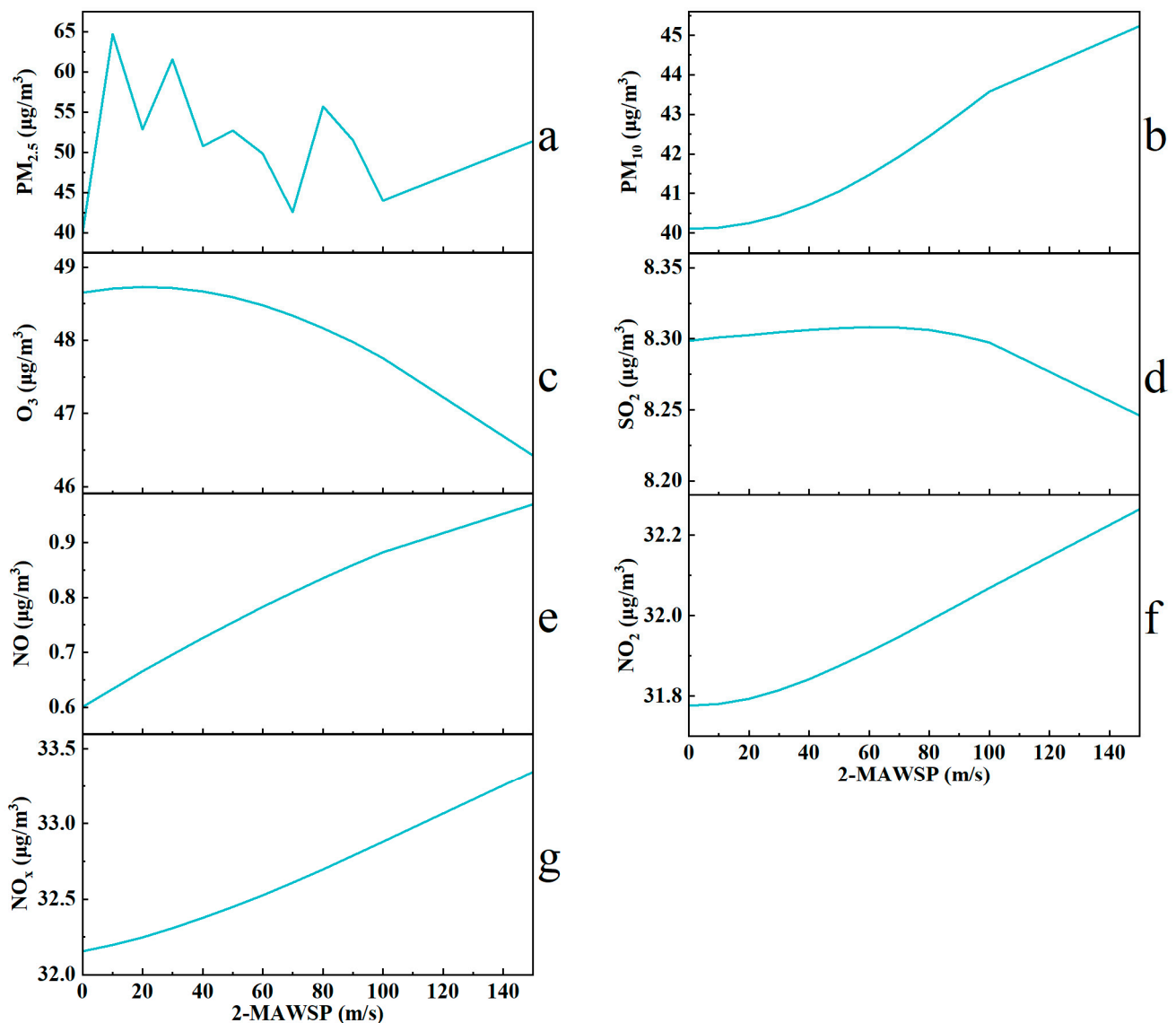


Figure 8. Effect of 2-MAWSP (unit m/s) on various pollution concentrations (unit $\mu\text{g}/\text{m}^3$). (a), the relationship between $\text{PM}_{2.5}$ concentrations and 2-MAWSP; (b), the relationship between PM_{10} concentrations and 2-MAWSP; (c), the relationship between O_3 concentrations and 2-MAWSP; (d), the relationship between SO_2 concentrations and 2-MAWSP; (e), the relationship between NO concentrations and 2-MAWSP; (f), the relationship between NO_2 concentrations and 2-MAWSP; (g), the relationship between NO_x concentrations and 2-MAWSP.

The response of the air quality parameters to 2-MAWSP as noted by the Informer model is shown in Figure 8. The figure shows that except for the SO_2 and O_3 concentrations, which decreased with an increase in 2-MAWSP, the concentrations of PM_{10} , NO , NO_2 , and NO_x all increased with an increase in 2-MAWSP, and they approximately exhibited a linear correlation with 2-MAWSP. However, as 2-MAWSP increased, the alteration in $\text{PM}_{2.5}$ concentration became notably more pronounced.

The response of the air quality parameters to 10-MAWSP as noted by the Informer model is shown in Figure 9. Unlike with 2-MAWSP, except for $\text{PM}_{2.5}$, PM_{10} , and O_3 , the concentrations of the other air quality parameters generally showed a downward trend with an increase in 10-MAWSP. Also, compared to the situation with 2-MAWSP, the concentration of PM_{10} initially decreased and then increased. The change in O_3 concentration was similar to that with 2-MAWSP, generally showing a parabolic shape. Moreover, different from the situation with 2-MAWSP, the concentrations of NO , NO_2 , and NO_x showed completely

opposite trends with an increase in 10-MAWSP. However, similar to the situation with 2-MAWSP, the fluctuation in $PM_{2.5}$ concentration was still quite drastic.

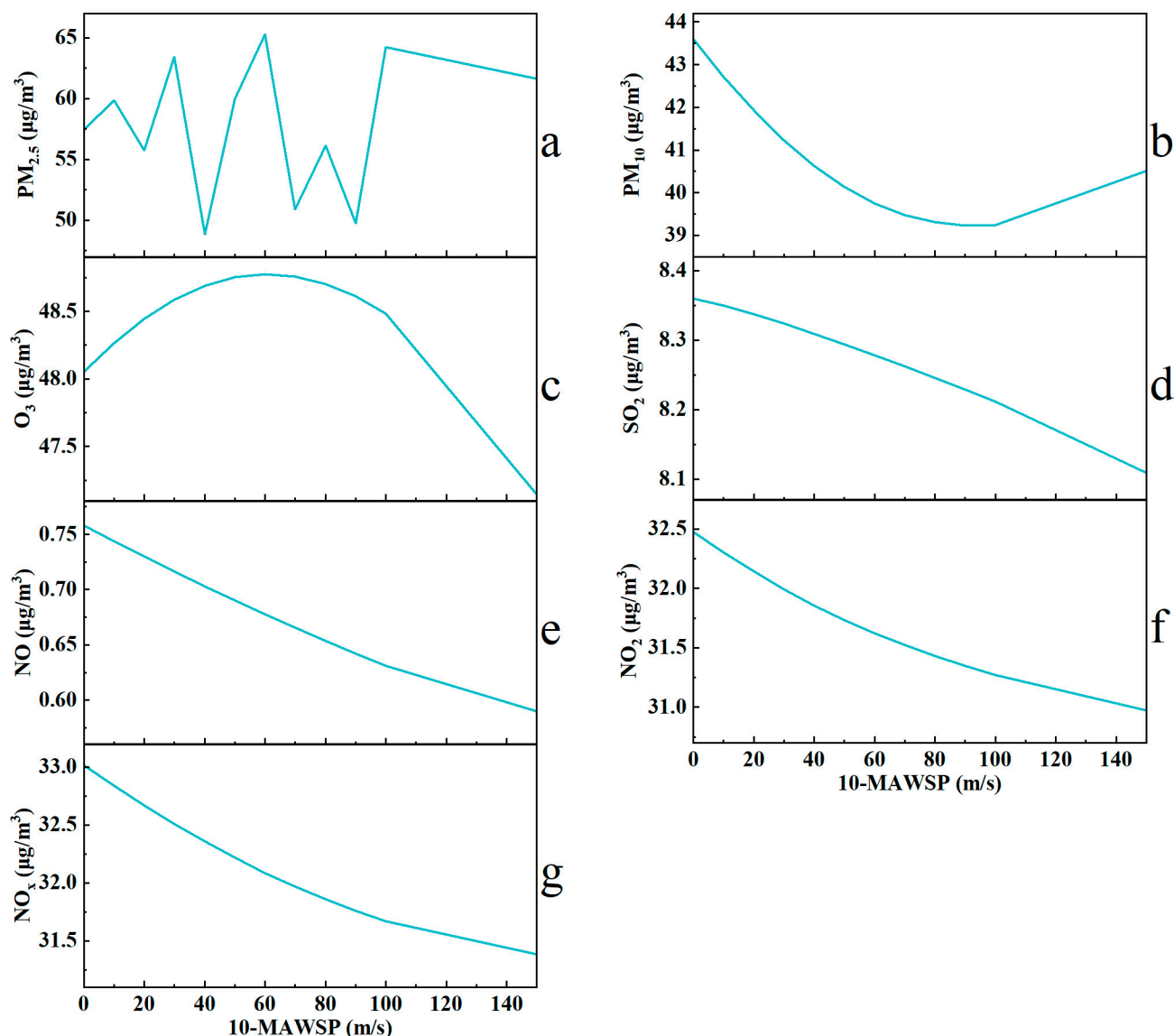


Figure 9. Effect of 10-MAWSP (unit m/s) on various pollution concentrations (unit $\mu\text{g}/\text{m}^3$). (a), the relationship between $PM_{2.5}$ concentrations and 10-MAWSP; (b), the relationship between PM_{10} concentrations and 10-MAWSP; (c), the relationship between O_3 concentrations and 10-MAWSP; (d), the relationship between SO_2 concentrations and 10-MAWSP; (e), the relationship between NO concentrations and 10-MAWSP; (f), the relationship between NO_2 concentrations and 10-MAWSP; (g), the relationship between NO_x concentrations and 10-MAWSP.

The response of the air quality parameters to MXSPD as noted by the Informer model is shown in Figure 10. According to the figure, the influence of MXSPD on air quality parameters was largely comparable to that of 10-MAWSP. This suggests that MXSPD and 10-MAWSP have similar effects on air quality parameters.

The response of the air quality parameters to HP as noted by the Informer model is shown in Figure 11. The graph shows that except for $PM_{2.5}$ and NO , with the increase in HP, the concentrations of SO_2 , NO_2 , NO_x , O_3 , and PM_{10} all showed a tendency to rapidly decrease and then level off. Among them, the decrease in PM_{10} concentration was the most significant, which is inferred to be due to the larger aerodynamic diameter of PM_{10} , making it more susceptible to rapid sedimentation by rain compared to $PM_{2.5}$. The concentration of

PM_{2.5} after a rapid decline to a trough showed a rebound and then a slow upward trend. In contrast, only the concentration of NO rapidly rose to a high level with increasing rainfall and then slowly decreased. Perhaps the impact of HP on PM_{2.5} is influenced by multiple factors. Meanwhile, HP may also stimulate NO emission sources, such as thunderstorms promoting NO release, but as rainfall continued, NO concentration ultimately decreased.

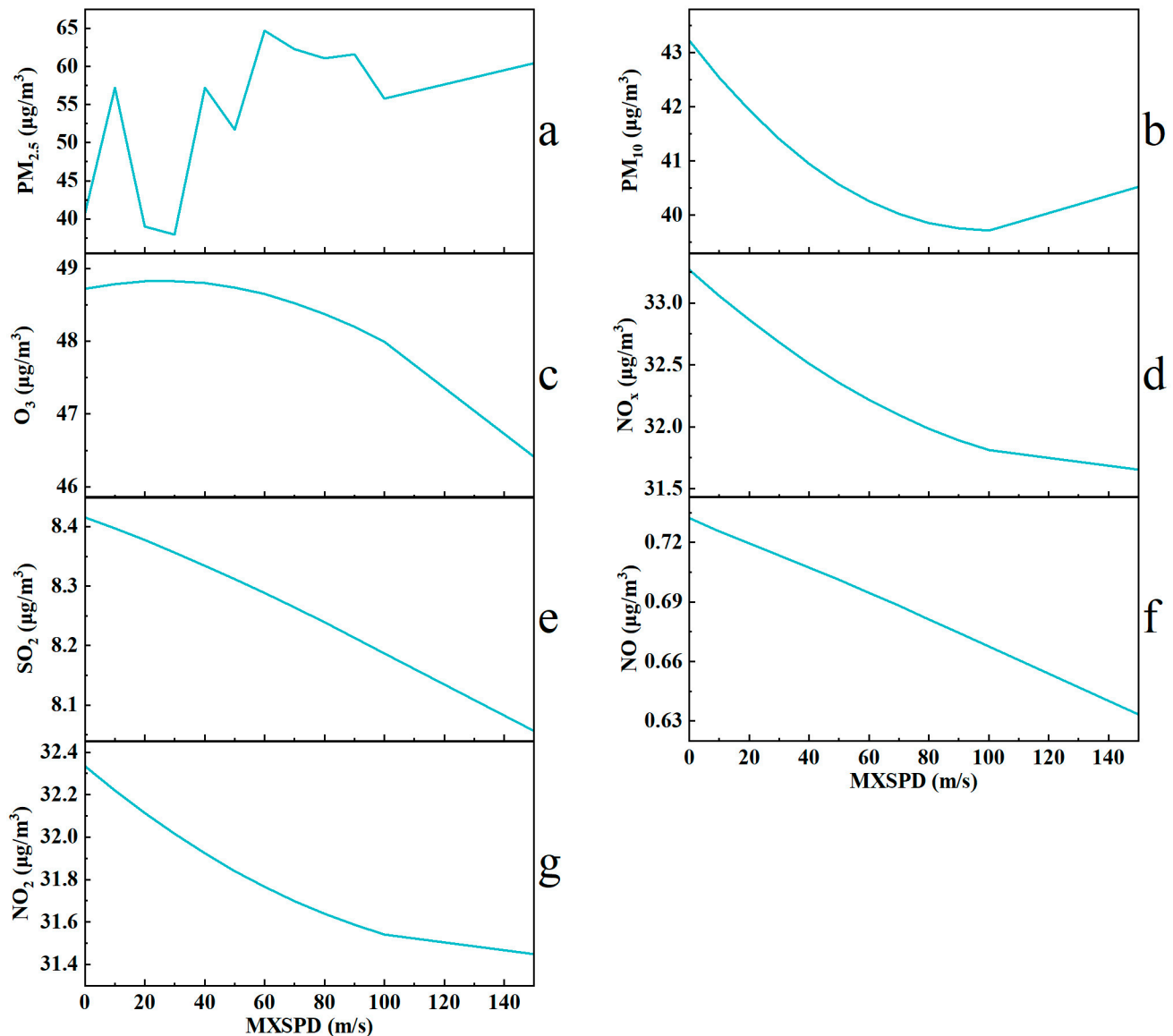


Figure 10. Effect of MXSPD (unit m/s) on various pollutions concentrations (unit µg/m³). (a), the relationship between PM_{2.5} concentrations and MXSPD; (b), the relationship between PM₁₀ concentrations and MXSPD; (c), the relationship between O₃ concentrations and MXSPD; (d), the relationship between SO₂ concentrations and MXSPD; (e), the relationship between NO concentrations and MXSPD; (f), the relationship between NO₂ concentrations and MXSPD; (g), the relationship between NO_x concentrations and MXSPD.

The response of the air quality parameters to AT as noted by the Informer model is shown in Figure 12. With the increase in AT, the concentrations of PM₁₀, NO₂, and NO_x generally showed a downward trend, with the PM₁₀ and NO₂ concentrations decreasing more significantly. The concentration of NO₂ decreased rapidly and then leveled off, while the PM₁₀ and NO_x concentrations rebounded after a rapid decline and then leveled off. Unlike PM₁₀, NO₂, and NO_x, the concentration of SO₂ first rose to a peak with the increase

in AT and then decreased until it leveled off. The concentrations of NO and O₃, overall, increased with the rise in AT. The concentration of NO first increased with the rise in AT and then leveled off, while the concentration of O₃, after a rapid climb to a peak, showed a slow decline until it leveled off. The concentration of PM_{2.5} still shows an oscillating trend overall.

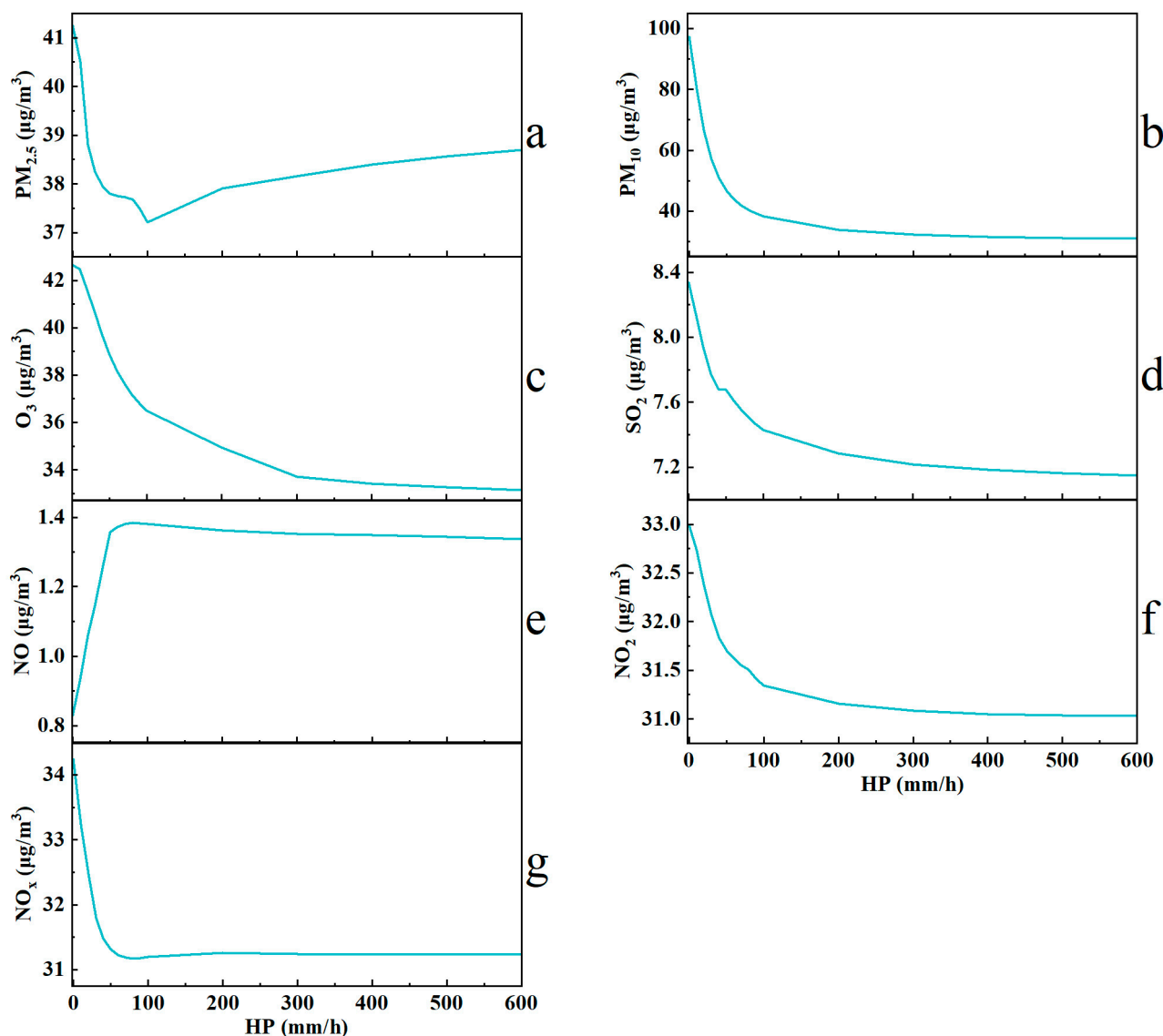


Figure 11. HP (unit mm/h) influence curve on various pollution concentrations (unit $\mu\text{g}/\text{m}^3$). (a), the relationship between PM_{2.5} concentrations and HP; (b), the relationship between PM₁₀ concentrations and HP; (c), the relationship between O₃ concentrations and HP; (d), the relationship between SO₂ concentrations and HP; (e), the relationship between NO concentrations and HP; (f), the relationship between NO₂ concentrations and HP; (g), the relationship between NO_x concentrations and HP.

The response of the air quality parameters to RH as noted by the Informer model is shown in Figure 13. With the increase in RH, the concentrations of SO₂ and PM₁₀ generally showed a downward trend, while the concentrations of NO, NO₂, and NO_x showed the opposite. It is inferred that with the increase in RH, the material transformation rate of SO₂ and PM₁₀ increased, leading to a decrease in concentration. As RH increased, the concentration of O₃ exhibited a pattern of initial rise followed by a decline. The concentration of PM_{2.5}, after a period of oscillation, showed a downward trend.

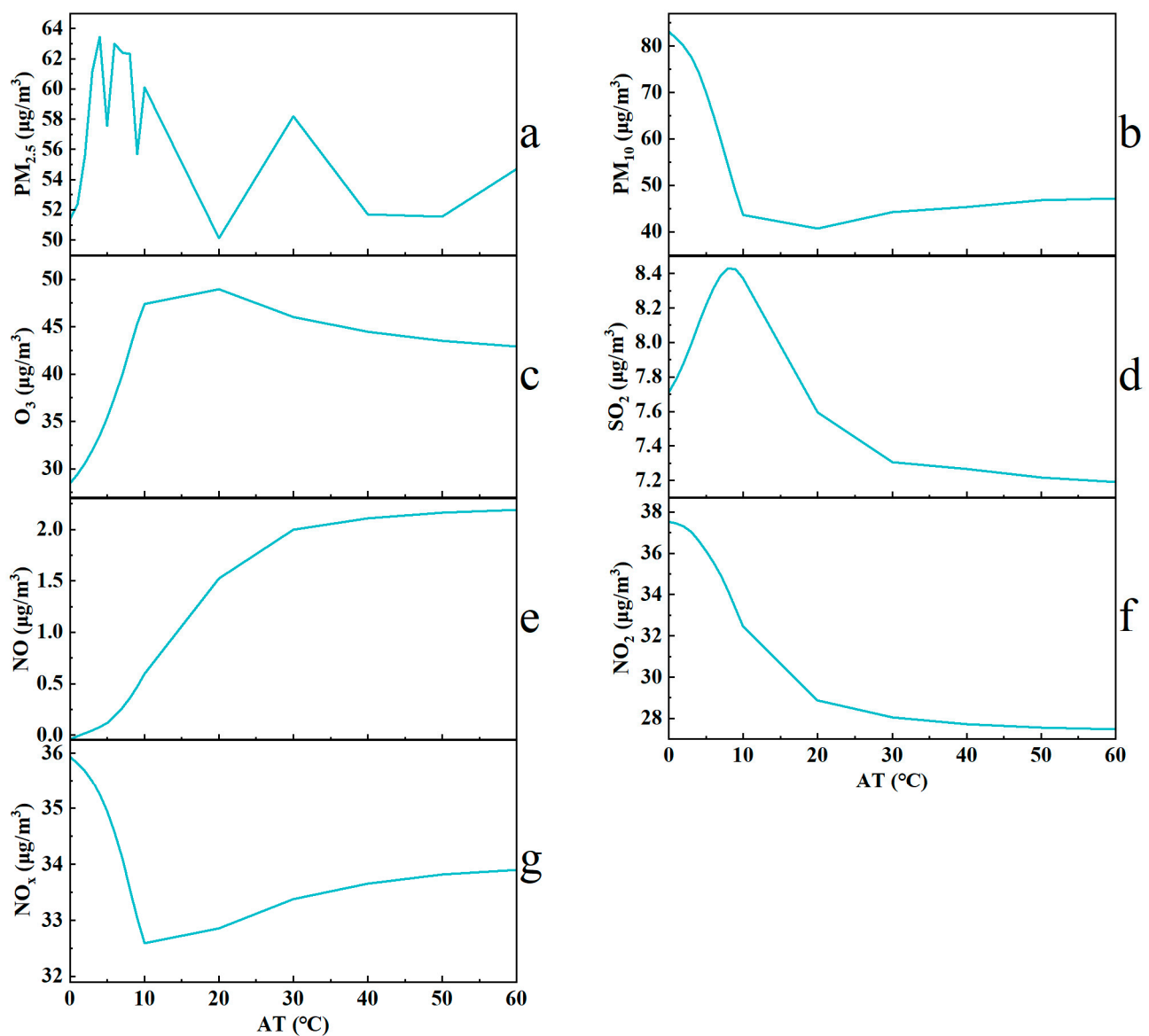


Figure 12. Effect of AT (unit °C) on various pollutants concentrations (unit $\mu\text{g}/\text{m}^3$). (a), the relationship between $\text{PM}_{2.5}$ concentrations and AT; (b), the relationship between PM_{10} concentrations and AT; (c), the relationship between O_3 concentrations and AT; (d), the relationship between SO_2 concentrations and AT; (e), the relationship between NO concentrations and AT; (f), the relationship between NO_2 concentrations and AT; (g), the relationship between NO_x concentrations and AT.

The response of the air quality parameters to STP as noted by the Informer model is shown in Figure 14. It can be seen that overall, with the increase in STP, except for the concentrations of NO and NO_x , which show a clear upward trend, the changes in other pollutant concentrations are more complex. The concentrations of PM_{10} and NO_x generally exhibited a tendency to decrease initially and then increase. Overall, as STP increased, the concentration of PM_{10} increased, and the magnitude was significant, while the concentration of NO_x generally decreased. In contrast, the concentrations of O_3 and SO_2 exhibited a tendency to rise initially and then fall with the increase in STP. The concentration of $\text{PM}_{2.5}$ experienced two significant fluctuations during the rise.

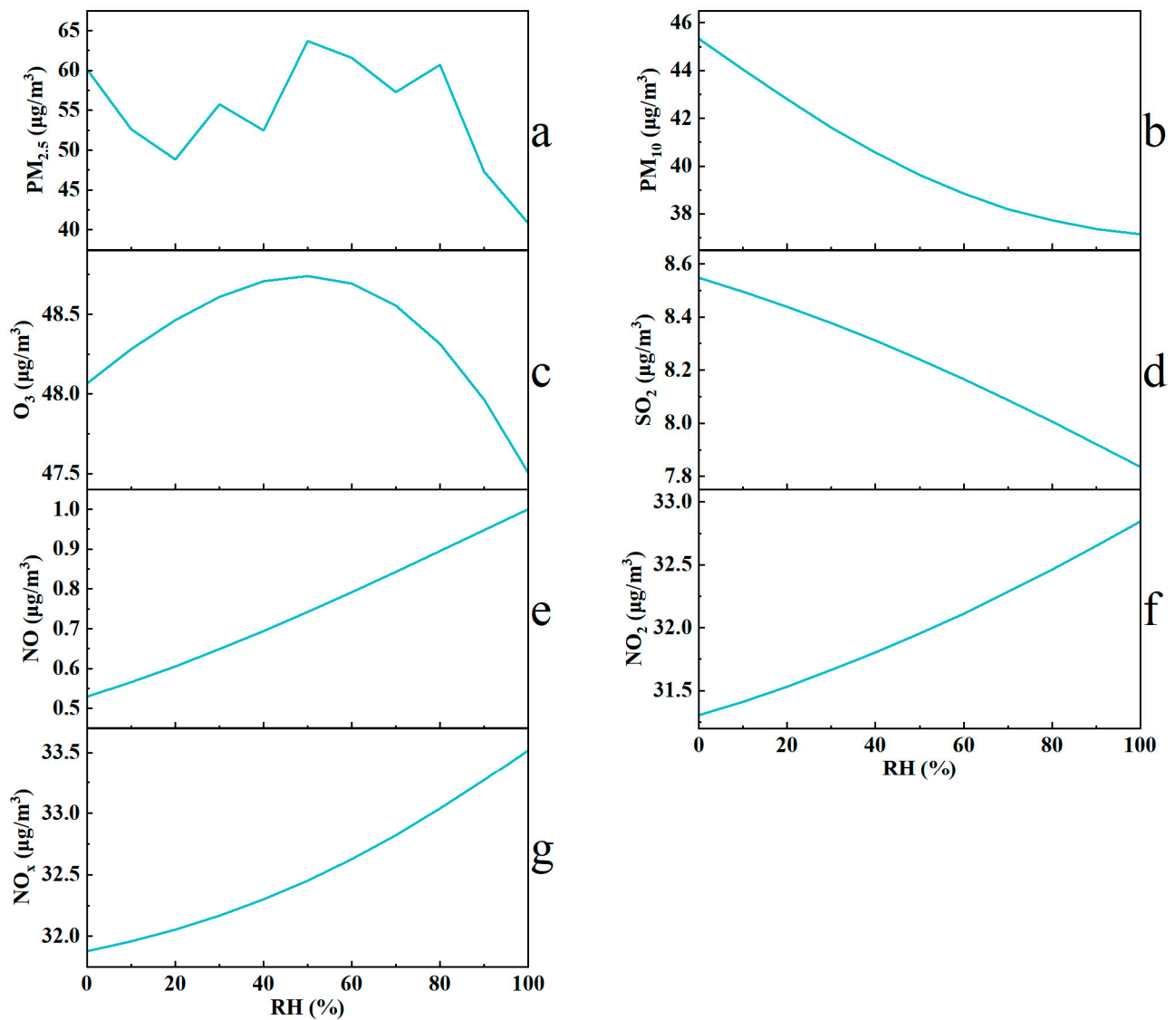


Figure 13. Effect of RH (percent content) on various pollutions concentrations (unit $\mu\text{g}/\text{m}^3$). (a), the relationship between $\text{PM}_{2.5}$ concentrations and RH; (b), the relationship between PM_{10} concentrations and RH; (c), the relationship between O_3 concentrations and RH; (d), the relationship between SO_2 concentrations and RH; (e), the relationship between NO concentrations and RH; (f), the relationship between NO_2 concentrations and RH; (g), the relationship between NO_x concentrations and RH.

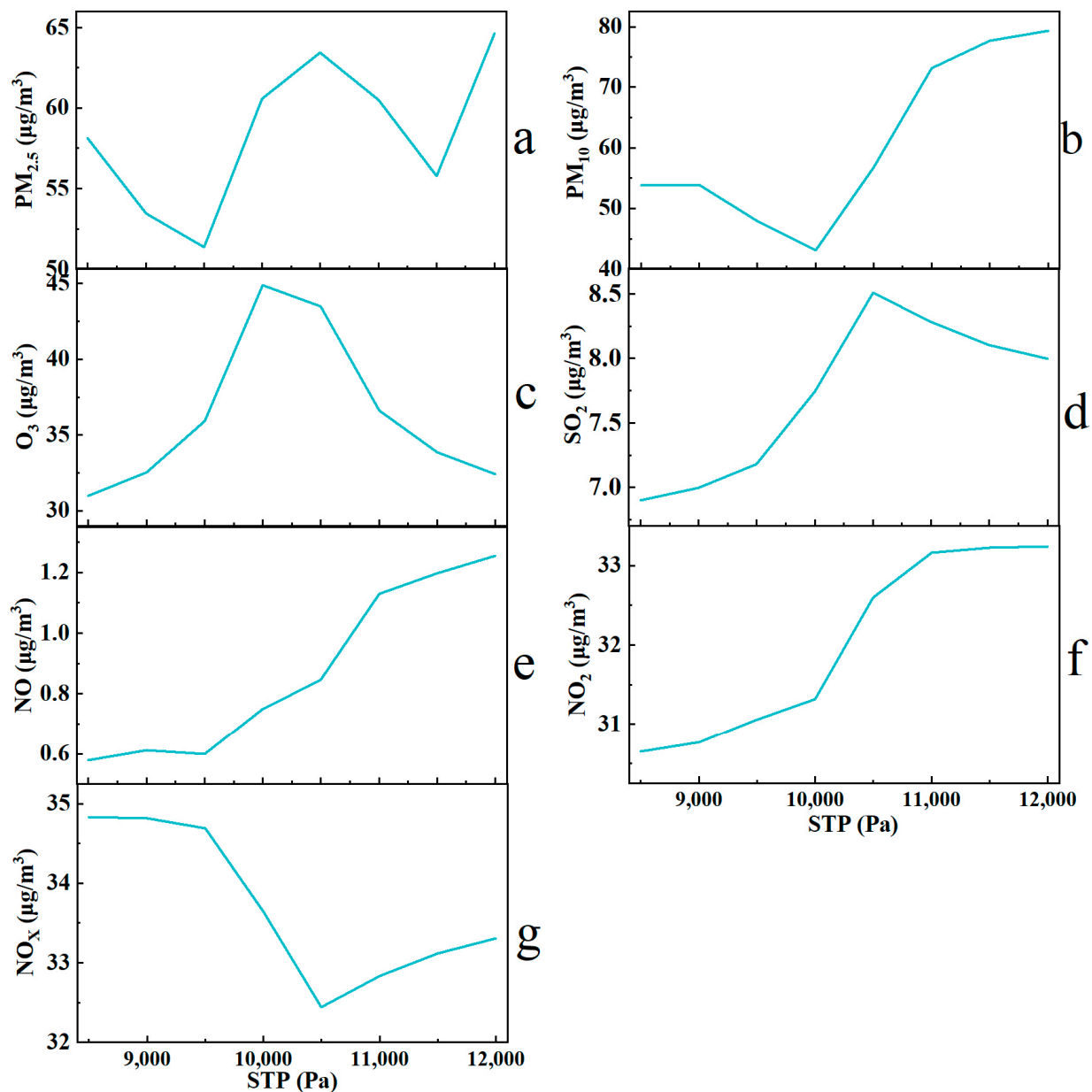


Figure 14. Effect of STP on various pollutants concentrations (unit $\mu\text{g}/\text{m}^3$). (a), the relationship between $\text{PM}_{2.5}$ concentrations and STP; (b), the relationship between PM_{10} concentrations and STP; (c), the relationship between O_3 concentrations and STP; (d), the relationship between SO_2 concentrations and STP; (e), the relationship between NO concentrations and STP; (f), the relationship between NO_2 concentrations and STP; (g), the relationship between NO_x concentrations and STP.

5. Conclusions

This paper utilized the Informer model to extract and save the response relation between air quality parameters and various meteorological factors, then selected samples to input into the model for testing, controlled a single variable sequentially, observed and recorded the changes in the model output, and obtained the quantified dependency responses between the air quality parameters and various meteorological factors saved in the model. The conclusions obtained from the tests are as follows:

- (1) The factor of wind has a significant dispersing effect on most air quality parameters. As the wind speed increases, the values of most air quality parameters decrease. For PM_{10} , as the wind speed increases, its concentration shows a tendency to decrease

initially and then increase. The primary cause of this phenomenon is that, with a high enough wind speed, dust particles are lifted from the ground, resulting in elevated levels of fine particulate matter concentration in the atmosphere.

- (2) HP has an extremely significant reducing effect on almost all air quality parameters. Moreover, the impact of HP has a significant influence on these air quality parameters, making them highly susceptible. During the initial phases of HP enhancement, notable alterations are observed in the measurements of air quality parameters. Afterwards, its transformation is gradual. Except for NO, all other air quality parameter values show varying degrees of decreases.
- (3) AT has a promoting effect on the increase in O₃ and NO concentrations. AT has a decreasing effect on the concentration of PM₁₀ and NO₂. For SO₂ concentration, AT has a promoting and then inhibiting effect.
- (4) RH has a reducing effect on the concentration of PM₁₀ and SO₂, while in contrast, RH has a promoting effect on the concentration of nitrogen oxides. For the concentration of O₃, it shows an initial increase followed by a decrease.
- (5) Overall, except for PM_{2.5}, O₃, and NO_x, STP has a promoting effect on the values of the other air quality parameters. For O₃, as STP increases, STP exhibits a promoting and then inhibiting effect on it. On the contrary, for NO_x, STP exhibits a first inhibitory and then promoting effect.

This study demonstrates the capability of the Informer model to learn and train air quality data along with meteorological data. It involves extracting and studying the response of variables in the trained model. This approach holds significance for investigating the responses between variables. The potential applications of this model can give some indications and assistance to meteorological and environmental departments in making appropriate decisions to improve air quality.

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Appendix A

Table A1. Air quality parameters.

Meteorological Factors	Abbreviations	Unit
Particulate Matter with an Aerodynamic Diameter Smaller than 2.5 µm	PM _{2.5}	µg/m ³

Table A1. Cont.

Meteorological Factors	Abbreviations	Unit
Particulate Matter with an Aerodynamic Diameter Smaller than 10 μm	PM ₁₀	$\mu\text{g}/\text{m}^3$
Sulfur Dioxide	SO ₂	$\mu\text{g}/\text{m}^3$
Ozone	O ₃	$\mu\text{g}/\text{m}^3$
Nitric Oxide	NO	$\mu\text{g}/\text{m}^3$
Nitrogen Dioxide	NO ₂	$\mu\text{g}/\text{m}^3$
Nitrogen Oxides	NO _x	$\mu\text{g}/\text{m}^3$
Carbon Monoxide	CO	mg/m^3

Table A2. Meteorological factors.

Meteorological Factors	Abbreviations	Unit
Maximum Instantaneous Wind Speed	/	m/s
Maximum Instantaneous Wind Direction	/	°
2-Minute Average Wind Speed	2-MAWSP	m/s
2-Minute Average Wind Direction	/	°
10-Minute Average Wind Speed	10-MAWSP	m/s
10-Minute Average Wind Direction	/	°
Extreme Wind Speed	/	m/s
Extreme Wind Direction	/	°
Maximum Wind Speed	MXSPD	m/s
Maximum Wind Direction	/	°
Hourly Precipitation	HP	mm/h
Air Temperature	AT	1/10°C
Maximum Air Temperature	/	1/10°C
Minimum Air Temperature	/	1/10°C
Relative Humidity	RH	%
Minimum Relative Humidity	/	%
Station Pressure	STP	Pa
Maximum Air Pressure	/	Pa
Minimum Air Pressure	/	Pa
Visibility	/	m
Minimum Visibility	/	m

Table A3. Other nomenclature.

	Abbreviations
Air Pollution Index	API
Seasonal-Trend Decomposition Procedure Based on Loess	STL
Convergent Cross Mapping	CCM
Detrended Fluctuation Analysis	DFA
Detrended Cross-Correlation Coefficient Analysis	DCCA
ρ Detrended Cross-Correlation Coefficient Analysis	ρ DCCA
Artificial Intelligence	AI
Auto-Regressive Moving Average	ARMA
Auto-Regressive Integrated Moving Average	ARIMA
Recurrent Neural Networks	RNNs
Long Short-Term Memory Network	LSTM
Spatiotemporal Transformer	STT
Long-Sequence Time Series Forecasting	LSTF
ProbSparse Self-Attention	PSSA
Self-Attention Distilling	SAD
Generative-Style Decoder	GSD

Table A3. Cont.

Abbreviations	
Masked Multi-Head ProbSparse Self-Attention	MMHPSSA
Multi-Head ProbSparse Self-Attention	MHPSSA
Fully Connected Layer	FCL
Mean Relative Error	MRE
Grey Relation Analysis	GRA
Mean Absolute Error	MAE
Root Mean Square Error	RMSE

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