Research on Air Quality Index Prediction Based on Neural Network
Taking Beijing as an Example

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Abstract—With the continuous improvement of the level of industrialization, the air pollution situation in China has become more and more serious. In many places, extreme weather such as haze has appeared, which seriously threatens people's health. Therefore, it is necessary to establish a scientific and reasonable air quality index prediction model. However, there are significant differences in air quality indices in different quarters, that is, the AQI values are significantly seasonal. Therefore, in order to improve the prediction accuracy, the data of different quarters are distinguished, and models of different quarters are established. In this paper, the principal component analysis method is used to analyze the correlation between API value and various meteorological factors, and the correlation factor is used as the input variable of neural network. The number of neurons in different quarters is determined according to the mean square error, and Bayesian normalization is established. The neural network is a model of the algorithm. Finally, the corresponding model was used to predict the air quality index of the corresponding quarter in 2018 based on the winter, spring, summer and autumn air conditions of Beijing from 2014 to 2017. The results show that the forecasting accuracy of each quarter is 88.27%, 92.28%, 94.04%, and 91.01%, respectively. The prediction accuracy of most studies is 70%–90%, and the prediction accuracy is high, which has certain reference value.

Keywords—neural network; air quality index; linear regression; principal component analysis; Bayesian algorithm

I. INTRODUCTION
The Air Quality Index (AQI) is an index that quantitatively describes the air quality status. The pollutants involved in the AQI index include six items such as PM10, PM2.5, SO2, NO2, CO, and O3 [1]. However, the air quality is not only affected by the above-mentioned pollutants, but also related to the local meteorological conditions. Under different meteorological conditions, even if the above pollutants are the same, the air quality may be different. At present, the research on environmental quality prediction includes: He Xiaoyun adds time parameter or momentum factor to neural network model [2], Zhang Huiyi uses universal gravitation search algorithm to improve neural network with prediction accuracy of 78.79% [3], Zhang Mengyao improved weighted Markov chain The accuracy of AQI prediction is 85.96% [4], and Niu Yuxia's relative error of genetic algorithm combined with neural network is 20%-40% [5]. Lin, Yi proposed a new air quality prediction algorithm based on cloud model granulation (CMG) and optimized the experimental parameters by grid search, reaching 71.43% prediction accuracy [6]. Kostas Karatzas established linear regression models and artificial neural network models, combined with random forest models for prediction [7]. J. Struzewska selected the parameters predicted by the GEM-AQ model as the predictors of the equation and used a representative time series to construct a regression function to predict the air quality [8]. Haiyan Chen proposed a method of uncertainty allocation (UA) for arbitrary prediction models to minimize the uncertainty of prediction results [9]. At present, the prediction accuracy of most studies is between 70% and 90%, which needs further improvement. At the same time, considering the neural network technology has good mapping ability for uncertain, multi-input and complex nonlinear problems, and superiority in forecasting, I establish a neural network prediction model based on Bayesian normalization algorithm [10].

In this paper, the principal component analysis method is used to analyze the correlation between API value and various meteorological factors and the mean square error to establish a neural network model based on Bayesian normalization algorithm. The model is used in winter and spring of Beijing from 2014 to 2017. Summer and autumn air conditions are the training samples for the corresponding quarterly air quality index for 2018.

II. BEIJING AIR QUALITY ASSESSMENT
According to the Beijing 2018 Air Quality Report, the statistics of Beijing's air quality status in 2018 are shown in "Fig. 1".
It can be found that the air quality in Beijing is mainly excellent, but there is also extreme weather such as heavy pollution. The total number of days above moderate pollution accounts for 15.3% of the whole year. In addition, Beijing SO₂ meets national standards (60μg/m³); NO₂ exceeds national standards (40μg/m³) 5%; PM10 exceeds national standards (70μg/m³) 11%; PM2.5 exceeds national standards (35μg/m³) 46%. Therefore, it is necessary to forecast the Beijing Air Quality Index to provide a basis for the treatment of air pollution.

III. DETERMINE FACTORS OF INFLUENCING AIR QUALITY

The air quality data used in this paper is derived from the data released by the post-weather report, including PM10, PM2.5, SO₂, NO₂, CO, O₃ and other data for each calendar year. The meteorological data comes from the global weather network, which contains a large amount of information such as temperature, wind level, wind direction and weather conditions (cloudy, sunny, rain, snow, etc.).

TABLE I. SYMBOLS AND MEANINGS OF VARIOUS METEOROLOGICAL FACTORS

| Factor | Mean               |
|--------|--------------------|
| X1     | Maximum temperature|
| X2     | Minimum temperature|
| X3     | Average temperature|
| X4     | Daytime weather    |
| X5     | Rainfall(snow) amount|
| X6     | Wind direction     |
| X7     | Wind power         |
| X8     | Relative humidity  |

In the acquired data, the wind direction and weather condition data are qualitative descriptions rather than magnitudes, making it difficult to make direct comparisons. Therefore, I require quantify these qualitative description factors to perform linear regression test [11]. The quantified values of weather conditions and wind direction are shown in "Table II" and "Table III".

The experimental data for linear regression test is the data from 2014 to 2017. Therefore, in order to better predict the API value, this section uses SPSS to analyze the correlation between API values and various meteorological factors for the meteorological characteristics, and to find the connection between API and various meteorological factors. The linear correlation between the API and each meteorological factor is described by calculating the Pearson correlation coefficient and the Spearma rank correlation coefficient. The calculation results are shown in "Table IV":

TABLE II. WEATHER STATUS QUANTIFICATION TABLE

| Weather | Heavy rain | Rainy | Thunder storm | Light rain | Sleet | Light snow | Sunny | Cloudy | Fog | Overcast | Smog |
|---------|------------|-------|---------------|------------|-------|------------|-------|--------|-----|----------|------|
| Quantity| 1          | 2     | 3             | 4          | 5     | 6          | 7     | 8      | 9   | 10       | 11   |

TABLE III. WIND VECTORIZATION TABLE

| Wind Direction | North | Northeast | East | Southeast | South | Southwest | West | Northwest |
|----------------|-------|-----------|------|-----------|-------|-----------|------|-----------|
| Quantity       | 1     | 2         | 3    | 4         | 5     | 6         | 7    | 8         |

TABLE IV. METEOROLOGICAL FACTORS RELATED TO AQI VALUES IN EACH QUARTER

| Season | Factor | Winter | Spring | Summer | Autumn |
|--------|--------|--------|--------|--------|--------|
|        |        | X1, X2, X3, X4, X5, X6, X7, X8 | X4, X5, X6, X7, X8 | X1, X2, X4, X6, X7, X8, X9 | X4, X5, X6, X7, X8 |

According to the AQI definition, in addition to the six factors of PM10, PM2.5, SO₂, NO₂, CO, and O₃ involved in air quality assessment, meteorological conditions will also affect air quality. According to the “New Compilation Dictionary”, meteorological factors include temperature, pressure, humidity and other phenomena and condensation, precipitation, wind, clouds, atmospheric light and other phenomena. However, in the actual experimental process, the study could not obtain all the factors. Therefore, I choose temperature, humidity, weather conditions, rainfall (snow) and wind as indicators of weather, that is, choose the highest temperature, the lowest temperature, the average temperature, the wind level, day and night weather conditions (such as rain, snow, yin, etc.), wind direction, wind, relative humidity, and rainfall (snow) as an alternative to the air quality model. The meteorological factors are shown in "Table I".
X1, X2, X4, X6, X7, X8, and X9 have good correlation with air quality index AQI, which is significant for AQI index. X4, X5, X6, X7, and X8 are related to air quality index AQI in spring.

First, the analysis is based on the corresponding candidate factors in four quarters to determine whether it is suitable for factor analysis. After analysis, the KMO values for the four quarters were found to be: 0.700, 0.550, 0.414, 0.624. According to the KMO metric given by Kaiser, it is known that the original factor in winter is suitable for factor analysis, while other quarters are not suitable for factor analysis.

### TABLE V. FACTOR TOTAL VARIANCE

| Factor | Sum    | Percentage of variance | Accumulated (%) |
|--------|--------|------------------------|-----------------|
| 1      | 2.971  | 37.14                  | 37.14           |
| 2      | 1.802  | 22.525                 | 59.67           |
| 3      | 1.278  | 15.969                 | 75.63           |
| 4      | 0.799  | 9.898                  | 85.62           |
| 5      | 0.72   | 9.003                  | 94.63           |
| 6      | 0.356  | 4.444                  | 99.07           |
| 7      | 0.045  | 0.564                  | 99.63           |
| 8      | 0.029  | 0.367                  | 100.00          |

For the winter neural network model, six factors including maximum temperature, minimum temperature, Z1 = 0.351 × X1 + 0.321 × X2 + 0.352 × X3 + 0.018 × X4 − 0.021 × X5 + 0.054 × X6 + 0.007 × X7 − 0.067 × X8. Z2 = 0.021 × X1 − 0.006 × X2 + 0.037 × X3 + 0.023 × X4 − 0.013 × X5 + 0.559 × X6 − 0.580 × X7 − 0.103 × X8. Z3 = −0.106 × X1 + 0.096 × X2 − 0.111 × X3 − 0.098 × X4 − 0.093 × X5 − 0.022 × X6 + 0.165 × X7 + 1.035 × X8. Z4 = −0.041 × X1 + 0.016 × X2 − 0.007 × X3 − 0.089 × X4 + 1.022 × X5 − 0.080 × X6 − 0.058 × X7 − 0.085 × X8. Z5 = 0.021 × X1 − 0.001 × X2 + 0.014 × X3 + 1.026 × X4 − 0.088 × X5 + 0.047 × X6 + 0.007 × X7 − 0.090 × X8

In summary, the factors affecting air quality include: 6 pollutants participating in the AQI index evaluation, namely PM10, PM2.5, SO2, NO2, CO, O3 and related meteorological factors.

### IV. NEURAL NETWORK BASED AIR QUALITY PREDICTION MODEL

The theory has proved that a BP neural network with only one hidden node can achieve arbitrary precision approximation for any nonlinear function. Therefore, from the perspective of simple and convenient training, only one hidden layer is generally selected. Moreover, as the number of hidden layers in the network increases, the reverse transmission efficiency of the error becomes very low, which is disadvantage for the learn of the neural network. Therefore, the neural network with only one hidden layer is used in the research.

According to the definition of AQI, the six factors of PM10, PM2.5, SO2, NO2, CO and O3 are the influencing factors of air quality. In the third section, SPSS is used to analyze the correlation between API value and various meteorological factors. Therefore, the input neurons of the winter model include: PM10, PM2.5, SO2, NO2, CO, O3, X1, X2, X3, X4, X5, X6, X7, X8; the spring model and the autumn model contain PM10, PM2.5, SO2, NO2, CO, O3, X4, X5, X6, X7, X8; summer model contains PM10, PM2.5, SO2, NO2, CO, O3, X1, X2, X4, X6, X7, X8, X9. The number of neurons in the model output layer is 1 (AQI value).

In general, the number of neurons in the hidden layer is determined by the following formula:

\[ n = \sqrt{n_i + n_0 + a} \]

(2)

Where:

- \( n \) — the number of nodes in the hidden layer
- \( n_i \) — the number of nodes in the input layer
- \( n_0 \) — the number of nodes in the output layer
- \( a \) — constant, value between 1 and 10

Therefore, the number of neurons in the hidden layer is between 5 and 14. In this paper, the mean square error (MSE) is the selection criterion of the number of neurons in the hidden layer: if the prediction performance of the network is

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**TABLE VI. MAIN COMPONENT COEFFICIENT TABLE**

| Factor | 1   | 2   | 3   | 4   | 5   |
|--------|-----|-----|-----|-----|-----|
| X1     | 0.351| 0.021| -0.106| -0.041| 0.021|
| X2     | 0.321| -0.006| 0.0966| 0.016| -0.001|
| X3     | 0.352| 0.037| -0.111| -0.007| 0.014|
| X4     | 0.018| 0.023| -0.0986| -0.089| 0.126|
| X5     | -0.021| -0.013| -0.093| 1.022| -0.088|
| X6     | 0.054| 0.559| -0.022| -0.080| 0.047|
| X7     | 0.007| -0.580| 0.165| -0.058| 0.007|
| X8     | -0.067| -0.103| 1.035| -0.085| -0.090|

It can be seen that the cumulative variance contribution of the first five factors has exceeded 90%, reaching 94.625%. Therefore, it can be considered that it is feasible to replace the original eight factors with the first five factors (Z1, Z2, Z3, Z4, Z5). Therefore, the principal component coefficients corresponding to the five factors Z1, Z2, Z3, Z4, and Z5 are shown in "Table VI"
unstable, the mean square error will be correspondingly larger; on the contrary, the prediction performance is stable. The formula for calculating the mean square error (MSE):

\[
\text{MSE} = \frac{1}{n} \sum_{i=1}^{n} (\hat{y}_i - y_i)^2
\]

(3)

Where \( \hat{y}_i \) represents the training result value and \( y_i \) represents the actual value.

The relationship between the implicit neuron and the mean square error is shown in "Fig. 2". The abscissa indicates the number of neurons in the hidden layer, and the ordinate indicates the corresponding mean squared difference.

Fig. 2. Hidden layer neurons and mean square error plots for each quarter.

It can be found that when the number of neurons in the hidden layer is 11 in the winter neural network system, the mean square error is the smallest at this time, that is, the prediction performance of the model is relatively stable; it is implicit in the spring neural network system. When the number of layer neurons is 12, the mean square error is the smallest. In the summer neural network system, when the number of neurons in the hidden layer is 6, the mean square error is the smallest; in the autumn neural network system, it is implied. When the number of layer neurons is seven, the mean square error is the smallest. Therefore, for different quarters, I establish different neural network models: the neural network model in winter is 11-11-1, the neural network model in spring is 11-12-1, and the neural network model in summer is 13-6-1, autumn. The neural network model is 11-7-1.

In addition, the implicit layer transfer function of this study is the "tansig-function"; considering the output as the air quality AQI index, the output transfer function selects the "purelin-function" [13].

V. EXPERIMENTAL RESULTS AND ANALYSIS
After filtering out the default value data, this paper forecasts the air quality index of the corresponding quarter in 2018 based on the winter, spring, summer and autumn air conditions of Beijing from 2014 to 2017. The correlation coefficient of training results and training is shown in "Fig. 3", "Fig. 4", "Fig. 5" and "Fig. 6".
Fig. 3. Comparison of training results and actual data for each quarter: Spring.

Fig. 4. Comparison of training results and actual data for each quarter: Summer.

Fig. 5. Comparison of training results and actual data for each quarter: Autumn.

Fig. 6. Comparison of training results and actual data for each quarter: Winter.
It can be found that the trained AQI value fits well with the actual air quality index. The training correlation is more than 0.995, and the training effect is better.

The predicted air quality index is compared to the actual AQI index. Among them, the error can be expressed as:

\[
\text{Error} = \frac{|\text{AQI actual} - \text{AQI forecasts}|}{\text{AQI actual}} \quad (4)
\]

Among them, the air quality index AQI value and actual value predicted by the neural network model in each quarter are shown in "Fig. 7", "Fig. 8", "Fig. 9" and "Fig. 10".

Fig. 7. Comparison of actual and predicted AQI: Spring.

Fig. 8. Comparison of actual and predicted AQI: Summer.

Fig. 9. Comparison of actual and predicted AQI: Autumn.

Fig. 10. Comparison of actual and predicted AQI: Winter.

The predicted air quality index is compared to the actual AQI index. Among them, the average error rate of winter prediction is 11.73%, the average error rate of spring prediction is 7.72%, the average error rate of summer prediction is...
prediction is 5.96%, and the average error rate of autumn prediction is 8.99%.

It can be seen from the above analysis that the air quality index obtained from the spring, summer and autumn predictions is in good agreement with the actual situation, while the winter prediction results are relatively poor.

VI. CONCLUSION

In this paper, a neural network model based on Bayesian normalization algorithm is established after determining the influence factor of air quality. The winter, spring, summer and autumn air conditions of Beijing from 2014 to 2017 are training samples for the corresponding quarter of 2018. The air quality index was predicted. It can be found that the forecasting accuracy of each quarter is 88.27%, 92.28%, 94.04%, and 91.01%, respectively. The prediction accuracy of most studies is 70%~90%, and the model prediction accuracy is high, which provides a model with higher prediction accuracy. It shows that BP network can be applied to Beijing's air quality forecast after effective training and has high prediction accuracy.

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