Identification Method of Urban Atmospheric Particulate Pollution Sources Based on Energy Spectrum Characteristics and Neural Network

Mingming Wang[1,a], Xiang Zhang[1*], Zhou Zhou[2,b]

[a]70964060@qq.com; * ntssthjj12369@163.com; [b]zhouz_dt@163.com

[1]Nantong Ecological Environment Monitoring Center, Nantong Jiangsu 226000, China
[2]Jiangsu Suli Environmental Technology Co., Ltd., Nanjing 210019, China

Abstract. Most of the pollution source identification mechanisms are set on the target structure, resulting in low identification efficiency and long response time for unit identification. To this end, a design and analysis method for identifying urban atmospheric particulate pollution sources based on energy spectrum features and neural networks has been proposed. According to the current experimental requirements, basic identification indicators for atmospheric particulate matter pollution sources are set, multi-level methods are used to improve recognition efficiency, a multi-level cross pollution source recognition mechanism is constructed, and an energy spectrum feature+neural network atmospheric particulate matter pollution source recognition model is designed. Urban pollution source recognition is achieved through distributed locking processing. The experimental results show that the five selected areas for identifying atmospheric particulate matter pollution sources have a response time of less than 0.3 seconds for final unit identification, which has good practical application effects. With the assistance and support of energy spectrum characteristics and neural networks, it has high pertinence and practical application value.

Keywords: Energy spectrum characteristics; Neural network technology; Atmospheric particulate matter; Pollution source; Pollution location; Identification method;

1. Introduction

Urban air pollution is difficult to identify and control, which involves pollutant location, type identification and other links, and the corresponding identification standards are also difficult to control, resulting in the final pollution source identification result is not true and reliable [1-3]. In recent years, with the extension of vehicle exhaust pollution, dust pollution, particulate pollution and other problems, urban air quality has greatly declined, especially Atmospheric Particulate Matters, which are not only difficult to control in a short time, but also have a huge impact range, and it is relatively difficult to identify [4] . The main reason for this problem is that there are many kinds of air pollution in cities at present. Although the relevant personnel have set corresponding solutions, the effect is very small [5] . Coupled with the influence of external environment and specific factors, it leads to the cross-diffusion of pollution, which further leads to the expansion of the scope of pollution and the harm to the surrounding environment [6] . In order to alleviate the above problems, the relevant departments have designed the identification method of urban atmospheric particulate pollution sources. This

IDEE 2023, November 24-26, Zhengzhou, People's Republic of China

DOI 10.4108/eai.24-11-2023.2343482

kind of pollution source identification forms are mostly independent structures, which can mark the specific location of the pollution source of pollutants within a reasonable range, and at the same time use the Internet to transmit the corresponding identification data and information to the designated location, laying the foundation for subsequent identification processing, orientation and analysis [7] . However, the pertinence and flexibility of this recognition method are low, and the recognition accuracy is also affected in different urban background environments [8-10] . And the traditional recognition structure is generally unidirectional, and the efficiency of recognition processing is low, which is also one of the important reasons for the error of the final recognition result. Therefore, the characteristic curve of particle energy distribution fluctuation formed by energy calibration of pulse amplitude of urban atmospheric particles based on energy spectrum characteristics and neural network is proposed. The neural network is an artificial neural network composed of biological neurons. Combining the above two technologies with the identification of urban atmospheric particulate pollution sources can, to a certain extent, further expand the actual scope of pollution source identification, strengthen the specific identification accuracy from multiple angles, design more flexible and changeable identification results, and improve the management and control of identification errors. In addition, with the help of energy spectrum characteristics and neural network technologies, hierarchical identification and control can be carried out in a targeted manner, which greatly improves the efficiency of overall pollution source location and marking, shortens the time for independent identification of local pollution sources, and provides reference and theoretical reference for the development and improvement of related technologies in the future.

2. Design the energy spectrum characteristics of urban atmospheric particulate pollution sources + neural network identification method

2.1. Set the basic atmospheric particulate pollution source identification index

The particle size can be roughly divided into single particle size and particle group size (generally referred to as average particle size) . For the particle size of a single particle, the particle density in the area is calculated by direct or indirect measurement method according to the settling speed of particles floating in the air, as shown in the following formula 1:

$$F = (m+n)^2 \times \mu n - \sum_{u=1} mu + \Im \tag{1}$$

In Formula 1: F indicate that density of particles in the area, m represents the coverage area, n represents a stacking area, μ indicate that settling speed of the unit, u represents the proportion of directional floating, $\Im$ Represents the single particle size . Combined with the above calculation, the calculation of particle density in the area is completed. Combined with the change of density, the equivalent diameter of the current particle size can be obtained. Subsequently, on this basis, it is necessary to set the particle swarm identification index and parameters, as shown in the following Table 1:

Table 1 Particle Swarm Identification Index and Parameter Setting Table

Setting of Particle Group Identification Indicator Names	Basic parameter standard value	Standard values of measured parameters
Average particle size change ratio	5.4	6.7
Distribution Function	11.36	15.24
Dispersity	65.35	80.47
Concentration representation division	Quantity concentration, mass concentration	Quantity concentration, mass concentration, settling strength
Proportion of controllable particles	3.1	4.3
Particle group diameter difference	0.025	0.011

2.2. Building a multi-level cross-contamination source identification mechanism

The traditional identification mechanism of atmospheric particulate pollution sources is mostly set to a one-way structure. Although it can achieve the expected identification tasks and objectives, it lacks pertinence and stability . In different background environments, the processing efficiency of identifying targets is low, which affects the processing and execution of subsequent identification work . Therefore, a multi-level cross-contamination source identification mechanism is designed, as shown in Figure 1 below:

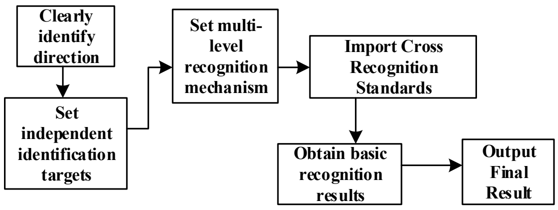

Figure. 1 Structural diagram of multi-level cross-contamination source identification mechanism

Combined with Figure 1, the design and practical analysis of multi-level cross-contamination sourc

2.3. Design an energy spectrum feature+neural network model for identifying atmospheric particulate pollution sources

Combined with the particle size, the weight method or light scattering method is used to calculatemass concentrationThe value of the conversion coefficient k is shown in the following formula 2:

$$P = \sum_{I=1} \chi I + \frac{(k+c)^2}{W} \times \theta I \tag{2}$$

In Formula 2: P express mass concentration conversion coefficient k value, χ indicates the dust concentration, I represents weight, W represents the coverage area, k represents the astigmatism region, c represents a repetitive fluctuation area, θ represents a non-uniform difference. Combined with the current test, complete the mass concentration calculation of conversion coefficient k. Subsequently, on this basis, through neural network technology, combined with the current situation of atmospheric particulate pollution in various regions of the city, a specific neural network identification hierarchy is designed, as shown in Figure 2 below:

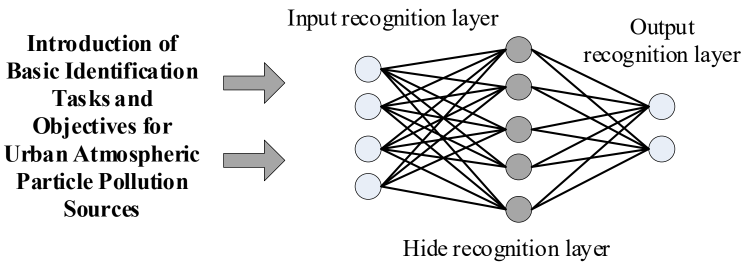

Figure. 2 The hierarchical structure diagram of urban atmospheric particulate pollution source identification based on neural network.

Combined with Figure 2, the hierarchical structure of urban atmospheric particulate pollution source identification based on neural network is designed. Then, in different identification levels, the identification targets of urban atmospheric particulate pollution sources are set, and a cyclic identification model structure is constructed. However, it should be noted that the identification target of the current design is not fixed, and corresponding adjustments can be made according to the actual identification requirements and standards to improve the flexibility of the model for the overall identification of atmospheric particulate pollution sources. Combined with the changes of the energy spectrum characteristic curve, the final identification accuracy of the model can be improved, and the optimization of the model and the internal pollution source identification framework can be completed.

2.4. Distributed locking processing to identify urban pollution sources

The so-called distributed locking processing is to clearly divide the corresponding distributed areas among cities on the basis of the above-mentioned design identification model, and optimize the final results by means of multi-dimensional dynamic location identification and locking of urban atmospheric particulate pollution sources. You can first set a basic recognition target in the current recognition program. Through intelligent model identification hierarchy and energy spectrum characteristics+neural network technology, the setting of distributed identification and locking processing index values is set, as shown in the following Table 2:

Table 2 Numerical Setting Table of Distributed Locking Processing Indicators

Distributed locking processing metrics	First phase	Phase 2
Unit recognition directional difference	0.35	0.16
Basic distributed locking time consumption/s	0.06	0.03
Distributed recognition fluctuation ratio	6.31	4.15
Directional identification controllable error	1.2	1.1
Equivalent diameter change ratio	6.8	7.8
Locked mean	16.38	18.44

Combined with Table 2, complete the setting of distributed locking processing index values. According to the order of the above model design, carry out distributed locking identification of atmospheric particulate pollution sources in the city, further clarify the specific location of pollution sources, and collect corresponding identification data and information during the process, which is convenient for later processing and analysis.

3. Method test

This time, the practical application effect of the identification method of urban atmospheric particulate pollution sources based on energy spectrum characteristics and neural network is mainly analyzed and verified. Considering the authenticity and reliability of the final test results, the analysis is carried out in a comparative way, and G city is selected as the main target of the test. The basic pollution data of the current city are collected by professional equipment and devices, and then collected and integrated for subsequent use. Next, according to the changes of current test requirements and standards, combined with energy spectrum characteristics and neural network technology, the basic test environment is related and built.

3.1. Test preparation

Combining the energy spectrum characteristics and neural network technology, the actual test environment of the identification method of atmospheric particulate pollution sources in G city is built and processed. At present, the basic test device can be set first. MATLAB software is used to design the simulation experiment, and it is connected to the city's environmental monitoring network to form a cyclic identification and processing environment for subsequent use. In view of the atmospheric particulate pollution in G city, the measured areas are divided into five, and the pollution situation in each area is different. Therefore, monitoring nodes are set in the area, and the nodes are interrelated to form a cyclic test structure. Using the acquired data and information, combined with neural network technology, the crossover probability of atmospheric particulate pollution source identification is calculated, as shown in the following formula 3:

$$M = \kappa^2 - \sum_{y=1} \Re y + \rho(1-j) \tag{3}$$

In Formula 3: M represents the cross probability of identifying atmospheric particulate pollution sources, κ indicates the range of variation, κ represents the conversion ratio, y indicates the number of directional identification times, ρ represents the number of iterations, j represents the fluctuation value of energy spectrum. Combined with the current test, complete the calculation of the crossover probability of atmospheric particulate pollution source identification, set it as the basic identification limit standard, and then adjust the test parameters of pollution source identification, as shown in the following Table 3:

Table 3 Adjustment Table of Test Parameters for Pollution Source Identification of Atmospheric Particulate Matter

Name of identification and testing indicators for atmospheric particulate matter pollution sources	Standard value of initial indicator parameters	Controllable parameter range setting
Identify mutation probability /%	12	10
Maximum allowable recognition error	1.2	1.1
Controllable recognition time consumption /s	0.25	0.16
Optimize identification objective function	10.3	16.7
Directional convergence value	11.05	15.24
Pollutant diffusion coefficient	3.02	4.15

Combined with Table 3, the test parameters of atmospheric particulate pollution source identification are adjusted. Based on this, the basic test environment is established and correlated. In the process, the energy spectrum characteristics and neural network technology are used to adjust the test environment reasonably for subsequent testing and practical verification analysis.

3.2. Method effectiveness verification

In order to evaluate the role of spectral features and neural networks in identifying atmospheric particulate matter pollution sources, an urban area with multiple pollution sources was selected as the experimental object. Set up monitoring nodes in this area and collect data on atmospheric particulate pollution. Divide the collected data into two groups: the experimental group and the control group. Extract energy spectrum features from the atmospheric particulate pollution data of the experimental group, and use neural network models for training and recognition. Record the identification results. The atmospheric particulate pollution data of the control group were directly identified without spectral feature extraction and neural network model training. Compare the accuracy and stability of recognition results between the experimental group and the control group.

The experimental group using spectral features and neural networks for identification showed higher accuracy in identifying pollution sources within the target area, which is consistent with the actual situation. The control group, which did not undergo spectral feature extraction and neural network model training, had relatively low recognition accuracy and had some errors compared to the experimental group. By analyzing the experimental results and comparing the recognition accuracy between the experimental group and the control group, it can be concluded that energy spectrum feature extraction and neural network model training play an important role in identifying atmospheric particulate pollution sources, enhancing the accuracy and stability of recognition, and verifying the effectiveness of the method.

3.3. Test process and result analysis

In the above-mentioned test environment, according to the energy spectrum characteristics and neural network technology, the selected atmospheric particulate pollution sources in G city are identified and tested. Use the deployed nodes to collect basic values and information. According to the selected test area, the floating state of atmospheric particles is measured by using the energy spectrum characteristics, and the current floating value is obtained and calculated. Then, on this basis, through the neural network technology, combined with the urban atmospheric particulate pollution source identification program, lock identification is carried out, and the unit identification response time is calculated as shown in the following formula 4:

$$A = \aleph \varpi - \sum_{e=1} \nu e + \frac{1}{\tau} \tag{4}$$

In Formula 4: A indicates the unit identification response time, $\aleph$ indicates the orientation recognition range, $\aleph$ indicate that difference in recognition mean, ν represents a particle concentration value, e indicates the recognition frequency, τ represents the maximum allowable recognition error. Based on current testing, genetic algorithm and positive matrix decomposition method are used as comparison methods 1 and 2, respectively, and the results are analyzed as shown in Table 4:

Table 4 Comparative Analysis Table of Test Results

Immediately select the identification area for atmospheric particulate matter pollution sources	Identifying mean difference			Unit identification response time/s		
	Proposed method	Compariso n method 1	Compariso n Method 2	Proposed method	Compariso n method 1	Comparison Method 2
Pollution source identification area 1	2.1	2.5	2.6	0.19	0.26	0.29
Pollution source identification area 2	1.9	2.3	2.5	0.26	0.31	0.35
Pollution source identification area 3	1.6	2.0	2.1	0.27	0.35	0.38
Pollution source identification area 4	2.6	3.0	3.2	0.13	0.18	0.21
Pollution source identification area 5	2.7	3.1	3.4	0.24	0.31	0.35

Based on Table 4, the experimental results were analyzed: the proposed method differs from the comparison methods 1 and 2 in terms of identifying mean differences and unit identification response time. For the selected five atmospheric particulate matter pollution source identification areas, the proposed method's final unit identification response time is controlled within 0.3 seconds, indicating that the currently designed urban atmospheric particulate matter pollution source identification method, with the help and support of spectral features and neural networks, has good practical application effects, high pertinence, and practical value.

4. Conclusion

The identification methods for atmospheric particulate matter pollution sources are relatively more flexible and diverse, with strong stability and specificity. In different background environments, with the assistance and support of energy spectrum features and neural networks, the identification methods for atmospheric particulate matter pollution sources are no longer single and fixed. Not only can the specific types of atmospheric particulate matter pollution be identified in the first time, but also the actual recognition range can be expanded, Conduct controllable management and linkage control from multiple perspectives.

Acknowledgements: The study was supported by Nantong Social Livelihood Science and Technology Project (No.MS22022051): Preparation and electrochemical response of functional mxene based conductive composites for rapid detection of contaminants in food.

References

[1] Xu P, Yang Y, Zhang J 2022 Characterization and source identification of submicron aerosol during serious haze pollution periods in Beijing. Journal of Environmental Sciences, 112(7521): 25-37.

[2] Shou Y , Meng T , Ai W ,et al. Conversational emotion recognition studies based on graph convolutional neural networks and a dependent syntactic analysis[J]. Neurocomputing, 2022, 501: 629-639.
[3] Shou Y, Cao X, Meng D. Masked Contrastive Graph Representation Learning for Age Estimation[J]. arXiv preprint arXiv:2306.17798, 2023.
[4] OtávioNunes dos Santos, Hoinaski L 2021 Incorporating gridded concentration data in air pollution back trajectories analysis for source identification. Atmospheric Research, 263(4): 105820.
[5] Pham V D, Fatimah M S, Sasaki A 2021 Seasonal variation and source identification of heavy metal(loid) contamination in peri-urban farms of Hue city, Vietnam. Environmental Pollution, 278(2): 116813.
[6] Zhu Y, Chen Z, Asif Z 2021 Identification of point source emission in river pollution incidents based on Bayesian inference and genetic algorithm: Inverse modeling, sensitivity, and uncertainty analysis. Environmental Pollution, 2021(8): 117497.
[7] Qiao P, Dong N, Yang S 2021 Quantitative Analysis of the Main Sources of Pollutants in the Soils Around Key Areas Based on the Positive Matrix Factorization Method. Environmental Pollution, 273(20): 116518.
[8] Moghaddam M B, Mazaheri M, Samani J M V 2021 Inverse Modeling of Contaminant Transport for Pollution Source Identification in Surface and Groundwaters: A Review. Groundwater for Sustainable Development, 2021(12): 100651.
[9] Dou J, Ma H 2022 Prediction of Building Energy Consumption Based on Ensemble Artificial Neural Networks. Computer Simulation, 2022(005): 039.
[10] Shou Y, Cao X, Meng D, et al. A Low-rank Matching Attention based Cross-modal Feature Fusion Method for Conversational Emotion Recognition[J]. arXiv preprint arXiv:2306.17799, 2023.