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ORIGINAL

INFLUENCE OF ATMOSPHERIC FINE PARTICLES POLLUTION ON PHYSICAL FUNCTION OF HIGH-INTENSITY SPORTS TRAINERS

Xiaodan Zhang

Zhengzhou Shengda University of Economics and Trade Management, He Nan, 450000, China
E-mail: mengdan331@163.com

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ABSTRACT

In recent years, the frequency of grey weather in North China has increased, which has seriously affected people's normal life. The increase of the concentration of atmospheric fine particles (PM2.5) is a landmark feature, and the harm of atmospheric PM2.5 pollution to human health has attracted more and more attention. High concentration of PM2.5 will not only lead to the decline of lung function, but also increase the incidence and mortality of respiratory diseases, and even affect people engaged in outdoor physical exercise. Firstly, this paper introduces the pollution status and harm of fine particles, as well as the technology and equipment adopted by the state for its monitoring at this stage, which has accumulated some prior knowledge for the establishment of soft sensing model. This paper systematically introduces the structure and learning process of BP and RBF neural networks, and determines the feasibility of establishing a soft-sensing model based on BP and RBF neural networks to conduct soft-sensing experiments on the concentration of fine particles in the atmosphere. The results show that the chemical component that contributes the most to the mass concentration of PM2.5 is nss-SO42-, accounting for 27.2%, followed by OM and NH4+, while the concentration of NO3- is low, accounting for only 4.4%. Generally speaking, per capita gas pollutant emissions decrease with the increase of per capita income. The estimated value of the proportion of the tertiary industry is sometimes not significant, but as long as it is significant, its symbols are all negative, which is in line with expectations, indicating that developing the tertiary industry is conducive to improving the environmental quality.

KEYWORDS: Fine particle pollution; Sports trainers; Environmental pollution

1. INTRODUCTION

With the rapid development of the global economy and the accelerating process of urbanization, the situation of air pollution has become more and more serious. At present, the most important urban air pollutant in China is atmospheric particulate matter (Liao ZhiHeng et al., 2017). The morphology and particle size of atmospheric particles are different and their components are very complex, and their complex components and morphology are directly related to human health (Shen et al., 2010). Atmospheric fine particles, that is, particles with a diameter of less than or equal to 2.5um from the perspective of dynamic aerodynamics, are the atmospheric particles that do the greatest harm to human body. This is because the specific surface area of atmospheric fine particles is larger than that of other atmospheric particles, and more harmful and toxic substances can be adsorbed. They can be deposited in human alveoli through human respiration, and even reach other organs through lung ventilation, which has a serious impact on human health (Xu et al., 2015). The high-speed development of China's economy over the past few decades has pushed forward the process of industrialization and urbanization. In this process, a large number of fossil fuels have been consumed. After the harmful exhaust gases such as dust produced by the combustion of fossil fuels are discharged into the atmosphere, China's air quality continues to deteriorate. Among them, atmospheric particulate pollutants have become the primary pollutant in China's urban air pollution, and the haze weather caused by atmospheric pollutant PM2.5, It has attracted the attention of the whole people, and therefore has become a hot spot of relevant scientific research. On the one hand, it will reduce the visibility of the atmosphere, affect people's normal work and life, and bring inconvenience to traffic; On the other hand, too high particle concentration increases the incidence rate of respiratory and cardiovascular diseases and brings serious health risks. These effects will increase significantly with the extension of pollution time (Fortelli et al., 2016). Because of the small particle size, fine particles can enter the bronchial wall of human body with respiration, interfere with the gas exchange in lung, and even penetrate alveoli into blood circulation, thus affecting the functions of human tissues and organs. In addition, fine particles can not only cause respiratory infections, but also significantly increase the probability of cancer. Good environmental quality is essential for people who take part in sports, which is not only beneficial to their health, but also improves their sports performance. On the contrary, bad sports environment will bring adverse effects to people's health. For the people who take part in sports, the worsening air pollution seriously threatens their health (Li et al., 2019). The impact of air pollutants on athletes' health is related to the concentration of pollutants, sports events, load intensity, time and their own lung level. Usually, high concentrations of air pollutants will seriously interfere with and damage the normal physiological functions of the body, while long-term and intensive training in the air polluted environment will make athletes' bodies bear greater pollution effects (Wang et al., 2018). If you exercise in an environment with air pollution, because the breathing pattern changes from single nose-breathing to mixed nose-throat and day-throat breathing during exercise, it will lead to the reduction of the filtering effect of the nasal cavity on the air, which significantly aggravates the harmful effects of air pollutants on human body. In order to maintain normal life activities and healthy physiological functions, the human body must breathe fresh gas from the external atmospheric environment, so the normal chemical composition of the air is an essential condition to ensure human health (Shen et al., 2010; Yang et al., 2016). The concentration of fine particles in the atmosphere is influenced by topography, emission source location, emission rate, meteorological environment and other factors, showing strong nonlinear characteristics.

Artificial neural network has strong nonlinear fitting ability and has great development space in the field of soft sensing. Among all network models, BP neural network and RBF neural network are the most studied and the most perfect network models (Martudi, 2023). In view of this, it is of great significance to establish a soft measurement model based on BP neural network and RBF neural network to explore the feasibility of realizing the soft measurement of the concentration of fine particles in the atmosphere, which is of great significance to reduce the pollution level of fine particles and strengthen the governance of the atmospheric environment. However, the research on healthy athletes is relatively rare, and the measured lung function indicators are not comprehensive. Outdoor environment is an indispensable sports place for people who take part in physical exercise, so they inevitably have to be exposed outdoors for a long time, especially for athletes who train systematically outdoors. The grey weather directly puzzles their normal sports training. Therefore, it is urgent to study the impact of fine particulate pollution in Taiyuan on athletes' health. Its innovation lies in:

(1) Analyze the current PM2.5 pollution situation in China, and explore the causes of pollution in China and the historical experience of developed countries. There are obvious regional differences in PM2.5 pollution in China, especially in North China with Beijing-Tianjin-Hebei as the core.

(2) Analyze the spatial effect of PM2.5 pollution in China from the perspective of spatial geography. From a national perspective, China's PM2.5 emissions are on the rise year by year. From the regional perspective, the eastern region is the main area of PM2.5 emissions in China, and its PM2.5 emissions account for 43.06% of the total national emissions.

(3) The improved correlation analysis is used to screen the influence factors of the pre-selected eight fine particles, and six influence factors which have great influence on the concentration of fine particles are selected as the input vectors of the soft-sensing model. On this basis, the operating results of the models are compared by experience and heuristics, and the parameters of BP and RBF network models are determined, so as to construct the soft sensor model with the best performance. This paper studies the impact of atmospheric fine particles pollution on the physical function of sports trainers. The framework is as follows:

The first chapter is the introduction. This part mainly expounds the research background and significance of fine particle pollution in the atmosphere and athletes' physical harm, and puts forward the research purpose, methods and innovation of this paper. The second chapter mainly summarizes the relevant literature, summarizes its advantages and disadvantages, and puts forward the research ideas of this paper. The third chapter is the method part, which focuses on the research methods of neural network for athletes' training time and environment and fine particles. The fourth chapter is the experimental analysis. In this part, experimental verification is carried out on the data set to analyze the performance of the model. Chapter five, conclusion and outlook. This part mainly reviews the main contents and results of this study, summarizes the research conclusions and points out the direction of further research.

2. Related Work

The research on the characteristics of particulate pollution shows that the pollution in winter is more serious than that in summer, and the pollution in heating period is more serious than that in non-heating period, but the particulate matter with different particle sizes in different regions is slightly different. The research shows that inhalable particulate matter PM10, especially PM2.5, can damage the respiratory system, destroy the immune system, cause respiratory system, cardiovascular and cerebrovascular diseases and other diseases, thereby increasing mortality (Astorino et al., 2018). The sources and compositions of atmospheric particles with different particle sizes have different impacts on the atmospheric environment and human health. At this stage, domestic research is mainly focused on PM10 and PM2.5, while the research on pm1.0 is relatively small (Mattei et al., 2018). Liao Z et al. (Liao ZhiHeng et al., 2017) got the localized MSEs through regression analysis, and reconstructed the extinction coefficient to get a better extinction fitting result (Dai et al., 2018). Guo et al. (Guo et al., 2020) briefly reviewed the research status of PM2.5 and its components and human health in recent years, starting from the effects of PM2.5 and its chemical components on respiratory system, cardiovascular system, cancer, reproduction and nervous system. Luo H (Luo et al., 2020) pointed out that there are differences in environmental health effects among countries or regions, and the differences in environmental health risks among countries or regions are subject to the differences in the level of public services such as education, environment and health in that country or region (Wang & Wang, 2024). In order to measure the important parameter of oxygen content in flue gas, Li Y et al., (Li et al., 2016) established a soft-sensing model of flue gas oxygen content based on neural network and statistical analysis on the basis of traditional technology, and compared it with the traditional soft-sensing method. The experiment shows that the established model has stronger measurement accuracy and fault-tolerant ability than the traditional method. On the basis of studying the algorithm and structure of artificial neural network, Shao et al., (Shao et al., 2017) established a neural network soft-sensing model to simulate and measure the distribution of NOx concentration in street canyons. The results showed that the linear correlation value between the model output of training samples and the actual value was 0.93, and that between the model output and the actual value of testing samples was 0.87, which had a good simulation measurement effect and could be applied to the soft-sensing calculation of NOx concentration in street canyons (Luo et al., 2020). Xu et al., (Xu et al., 2015) characteristics of organic and elementary carbon in PM2.5 and others systematically defined the definition and source of particulate pollutants. Scholar studied the effects of heavy metals in particulate matter on cardiovascular diseases, and the results revealed that heavy metals carried by atmospheric particulate matter may be related to the onset of cardiovascular diseases (Foster et al., 2015). Shao et al. (Shao et al., 2017) collected the annual average concentration of PM10 in 113 important cities in China, and after comparing the health data of residents in cities, they revealed that PM10 in the atmosphere caused serious losses to the health of residents in cities, or caused premature death of patients, medical outpatient, hospitalization for cardiovascular diseases, or respiratory diseases (Salazar-Martínez et al., 2018). In the article "Re-recognition of the concept, structure system and scientific regulation of load, load intensity and total load", X C deeply studied the definitions of load, load intensity and total load by using the method of literature. He defined load intensity from two different angles, and considered that load intensity is the stimulation of the load that athletes can bear in every minute or hour and complete a coherent movement, and load refers to the endurance of athletes under certain external stimulation (Alahmari et al., 2015). Kenneth believes that the amount of exercise is the physiological load provided by the human body during the exercise process, which consists of two aspects (Rundell, 2012): quantity and intensity, and quantity is the total number of groups, total time and total height required to complete the exercise (Chen et al., 2020). Dai Q expounded the relationship between different heavy loads and the variation of athletes' stocking rate (Dai et al., 2018). He found that in the process of increasing loads, athletes' stocking rate dropped most obviously after a long period of exercise (Heir & Larsen, 1995).

3. Methodology

3.1 Analysis of atmospheric fine particles by neural network combined with BP algorithm

At present, PM2.5 is one of the major air pollutants that mainly affect public health in China. PM2.5 concentration in the atmosphere may irritate eyes and respiratory tract, making people prone to pneumonia, bronchitis and other diseases, and at the same time may aggravate cardiovascular diseases. In many cases, air pollutants also have diffusion effect, and respiratory diseases of residents in urban areas are largely one of the results of air pollution. The influence of PM2.5 on public health is mainly through respiratory tract, and a small part of PM 2.5 enters human body through digestive tract. After PM2.5 particles enter the human body, it may harm the respiratory system of the human body and induce various diseases such as asthma. In addition, PM2.5 particles may cause lung disease, heart disease, respiratory diseases, etc. Therefore, PM2.5 pollution has a great impact on the elderly, children and other sensitive groups. The health end effects of major air pollutants are shown in Table 1.

Table 1: Health end effects of major air pollutants

AIR POLLUTANTS	HEALTH TERMINAL EFFECT
SO2	Total mortality, respiratory disease mortality, cardiovascular disease. Outpatient number, respiratory symptoms, pulmonary function, number of COPD inpatients
PM 25 PARTICULATE MATTER	Acute effects: daily mortality, respiratory symptoms, pulmonary function symptoms, daily outpatient number, bronchial disease Chronic effects: life expectancy, lung function, bronchial disease
NOX	Mortality, lung function, respiratory diseases

The basis of various effects of atmospheric particulate pollutants depends on their physical and chemical properties. Physical properties mainly include particle size and concentration; The chemical properties mainly depend on the chemical composition of particulate pollutants. Particle size is one of the most important physical properties of atmospheric particulate pollutants. Particle size determines its suspension time in the air, its location into the human body, and the specific surface area used to adsorb harmful substances. After entering the human body, atmospheric particulate pollutants will harm human health through breathing, eating and skin surface pores, especially breathing. As shown in Figure 1.

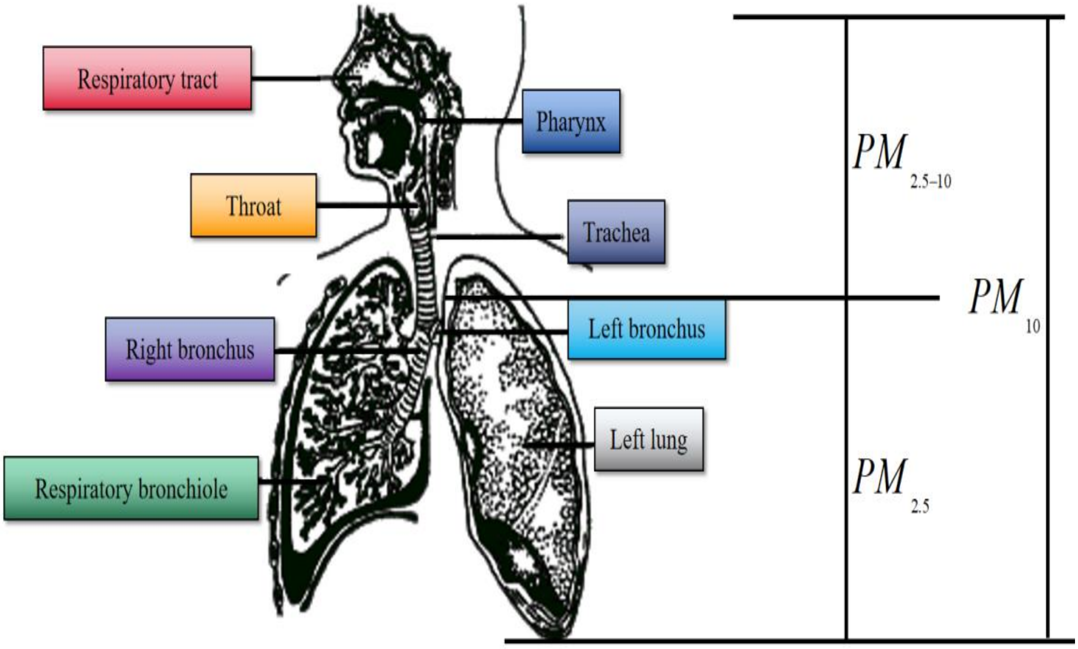


Figure 1: Schematic diagram of the route of atmospheric particulate pollutants entering the human body

Atmospheric particulate pollutants will enter the body through the respiratory system of the human body, starting from the nose and mouth, passing through the pharynx, larynx, organs, bronchi and alveolar ducts, and finally entering the alveoli. Some of the smaller particles will enter the blood with the gas exchange in alveoli, causing systemic harm with blood circulation. The smaller the particle size, the longer it stays in the atmosphere, and the greater the chance of being inhaled by the human body. Similarly, the smaller the particle size, the larger the surface area, the more pollutants it absorbs, and the greater the toxicity to the human body. The threat of atmospheric particulate pollutants to human health has been the consensus of many researchers. Due to the small particle size of particulate pollutants and the large amount of harmful substances carried on the surface, particulate pollutants will lead to various health risks such as cardiovascular diseases and respiratory diseases after entering the human body. Unfortunately, the specific pathogenic mechanism of atmospheric particulate pollutants is still controversial in academic circles, and a unified conclusion has not yet been reached. However, at present, the more convincing viewpoints include inflammatory reaction, oxidative damage, mutagenicity and carcinogenicity.

3.1.1 The calculation process inside the neural network

(1) define each variable, parameter and function; (2) Set the sample by operation, and output it by all levels after training by neural network; (3) Observe the training conditions to see if they meet the requirements; (4) After the training of neural network, transfer it to genetic algorithm. The learning flow chart of BP neural network is shown in Figure 2.

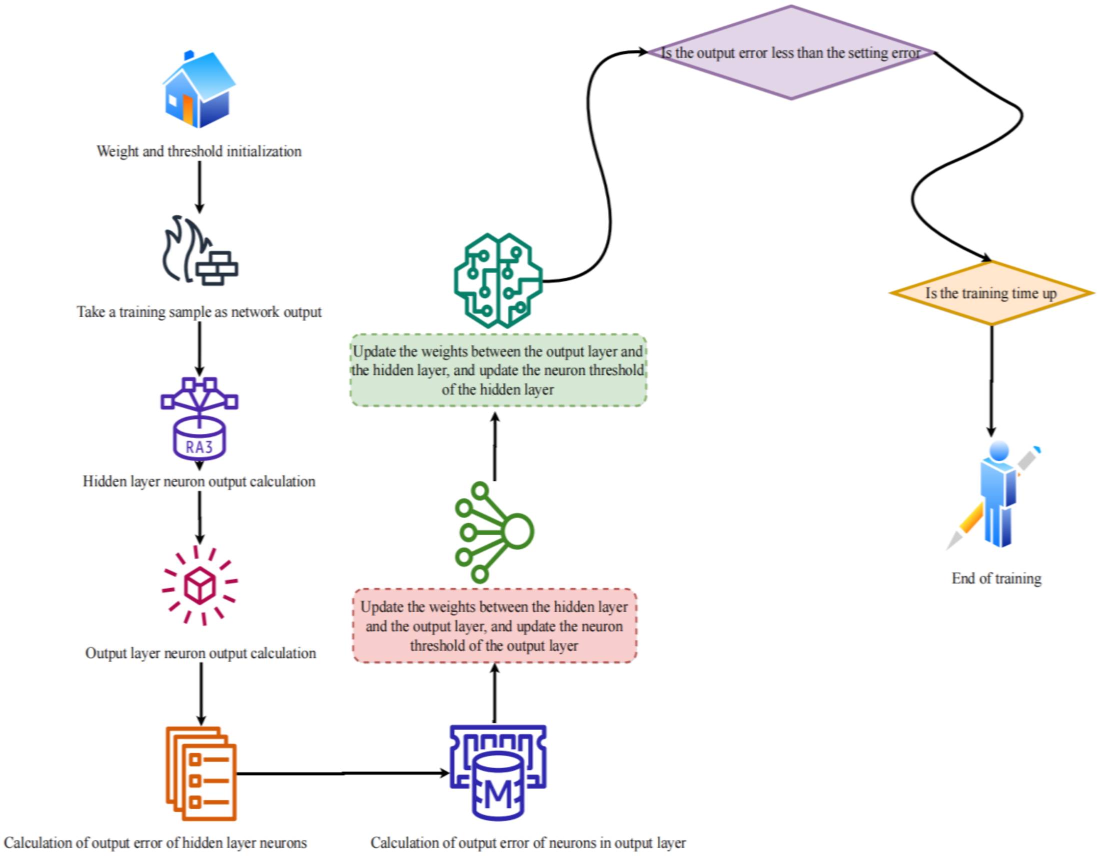


Figure 2: Learning flow chart of neural network

3.2 Optimization of fine particle pollution environment based on BP neural network

Neural network is essentially a numerical operation model, which is composed of a large number of neurons connected by weights, and each neuron represents a specific transfer function. Through the mapping training of a large number of input and output data, the internal characteristics of the data are stored by the weight of the network in the way of "memory", so as to realize the functions of nonlinear processing and complex logical operation of input and output data. The creation process absorbs many advantages of the information processing process of the human brain nervous system. Compared with the traditional system, the main features are: (1) Parallel and distributed processing capability of information. Neural network is composed of a large number of neurons connected with each other, and each neuron can carry out separate operation and transmission of information. (2) Highly nonlinear processing capability. As far as we know, at this stage, linear structure has been difficult to meet the requirements of users for information processing due to its own defects. (3) Good self-learning and self-organization function. (4) It does not depend on accurate mathematical models. Neural networks do not need to analyze the complex motion laws of specific processes, and use known theorems and laws to establish accurate mathematical models. (5) Good fault tolerance, association, synthesis and promotion ability. The neural network permeates the internal characteristics of data into the internal connections of the whole network. When the processed information is partially lost, blurred or wrong, the neural network will not affect the overall performance of the network through its strong ability of anti-noise and popularization. BP neural network is a typical hierarchical multilayer neural network, and its structure includes input layer, hidden layer and output layer, in which there is only one input layer and one output layer, and the hidden layer can have one or more layers. Each layer is composed of different numbers of neurons, and the upper and lower neurons are fully connected to realize information transmission, while the neurons in the same layer have no connection or information transmission. Figure 3 is a typical three-layer BP neural network structure diagram.

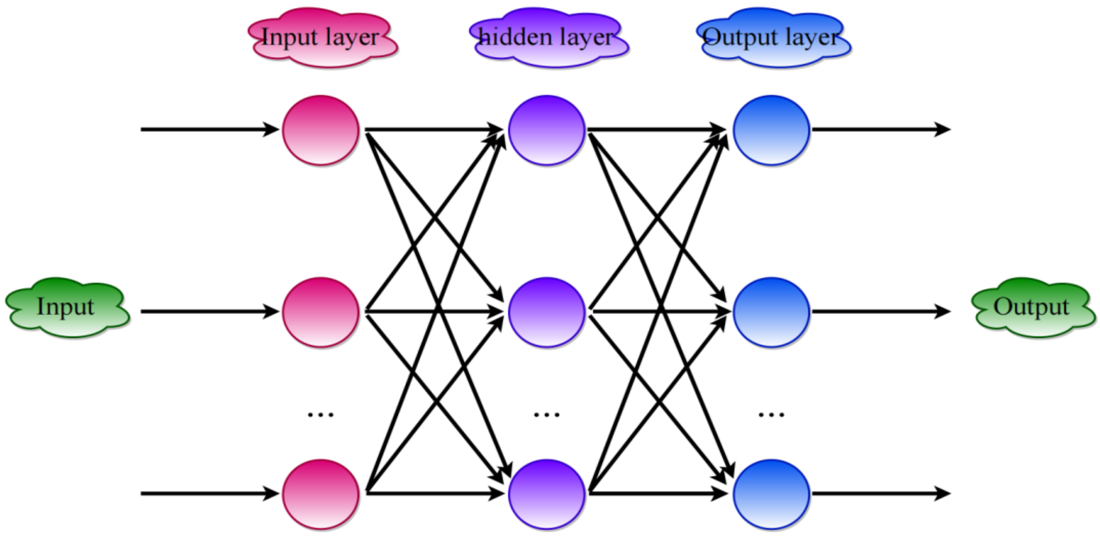


Figure 3: typical three-layer BP neural network structure diagram

The transfer function between input layer and hidden layer is Gaussian function. Gaussian function is a local response function. When the input signal is close to the center of the function, the function will produce a large output. When the input signal is far from the center of the function, the function output is zero. In all the data collected, we take SO2 concentration, NO2 concentration, PM10 concentration, air temperature, air pressure, relative humidity, wind direction and wind speed as the pre-selected input factors for establishing the network model, and the corresponding fine particle concentration as the output data of the network model. The actual situation shows that there are many unusable data in the collected original data sets. For some reasons, it is inevitable that some data in these data sets will be partially missing, mismatched, with large error deviation, confusion and repetition. Therefore, it is necessary to clean up the collected original data sets and select the correct data sets that are conducive to modeling. After cleaning up, 60 groups of data are finally selected as the data set used in the soft sensor modeling experiment. During the experiment, the data set is divided into the following parts:

(1) training set, which is used for the training of soft sensor network model. (2) The verification set is used to verify the training status of the soft sensor network model. (3) The test set is used to test the performance of the soft sensor network model. A Semiparametric Generalized additive model was used to analyze the effects of atmospheric particles with different particle sizes on daily hospitalizations of respiratory diseases and cardiovascular and cerebrovascular diseases Compared with the total population, the admission of patients with respiratory diseases and cardiovascular and cerebrovascular diseases belongs to a small probability event, and its actual distribution is similar to the Poisson distribution. Therefore, this study adopts the BP model of Poisson regression. On the basis of eliminating the day of the week effect and the long-term trend, meteorological factors and other confounding factors with spline smoothing function, the concentrations of PM10, PM2.5 and PM1.0 from 1 day to 7 days ago were introduced into the model. The specific model is as follows:

$$\log[E(Y_k)] = a + DOW + \beta X_k + s(\text{ time}, df) + s(Z_k, df) \quad (1)$$

Where, Y_k is the number of hospital admissions for respiratory diseases or cardiovascular and cerebrovascular diseases on the k day; $E(Y_k)$ is the expected number of hospital admissions on the k day; Is the residual; a is the regression coefficient; β is the particulate matter concentration on the X_k day; s is spline smoothing function; df is the degree of freedom; DOW is dummy variable of week dummy; time is the calendar time; Z_k is the k meteorological element. Then, Akaike information standard is used as the evaluation standard, and factor selection and goodness of return model are tested.

3.3 Spatial segregation index Model Based on Neural Network

Due to the complexity of PM2.5 emission sources and calculation, few studies have carried out accurate calculation of PM2.5 emission. However, the control of PM2.5 pollution needs to start with the reduction of PM2.5 emissions, so it is very important and meaningful to calculate the PM2.5 emissions in various regions in that year. At present, only MEIC, China's multi-scale emission inventory model constructed by Tsinghua University, has measured the national PM2.5 emissions, but it only published the data of 2008 and 2010. Considering the needs of research, this paper calculates the PM2.5 emissions in various regions of China with reference to the MEIC model calculation method and the "technical guide for the preparation of atmospheric fine particulate matter (PM2.5) source emission inventory". The main calculation methods are as follows:

$$Q_{\text{om } 2.5} = \sum_{j,k,m} \left[A_{j,k,m} \times EF_{j,k,m} \times R_{j,k,m} \times \left(1 - \eta_{j,m}\right)\right] \quad (2)$$

Where, $Q_{\text{om }2.5}$ represents the emission of PM2.5; j, k, m refers to the industry type of pollution emission (j), the fuel consumption type(K) and the technology type used for pollutant control (m) respectively; EF represents the emission coefficient of PM2.5, that is, the PM2.5 emission per unit energy consumption (in coal equivalent) of the emission source of a certain industry; *R* represents the distribution rate of a pollution control technology in a certain industry; Indicates the decontamination efficiency of an industry.

Spatial dislocation analysis was initially used to study the spatial allocation of labor. The spatial separation index model studies the spatial mismatch between public transport and labor in Singapore. Later, spatial separation was also applied to urban housing, pollution emissions and economic development. Based on the existing research results, this paper constructs the spatial separation index of atmospheric PM2.5 emission and pollution. The main calculation formula is as follows:

$$\begin{aligned} SMI &= \frac{1}{2P} \times \left[\left| \frac{G_1}{G} P - P_1 \right| + \left| \frac{G_2}{G} P - P_2 \right| + \cdots \left| \frac{G_n}{G} P - P_n \right| \right] \\ &= \frac{1}{2P} \sum_{i=1}^{n} \left| \frac{G_i}{G} P - P_i \right| \end{aligned} \tag{3}$$

Where, SMI represents the spatial segregation index value of PM2.5 emission and pollution. When the value of SMI is greater than 1, it indicates that there is spatial separation phenomenon. The larger the value, the more serious the spatial separation phenomenon is. P indicates the emission of PM2.5 per unit area in the whole country(tkm^{-2}); n indicates the number of provinces; P_i indicates the emission of PM2.5 per unit area in the i province; (tkm^{-2}) indicates the average concentration of PM2.5 in the national atmosphere; G indicates the average concentration of PM2.5 in the atmosphere of the i province. From the above formula, the contribution of the i province to the space segregation index is (R_i),and its calculation formula is as follows:

$$R_i = \frac{\left[\frac{1}{2P} \left| \frac{G_i}{G} P - P_i \right| \right]}{SMI} \times 100\% \tag{4}$$

According to the PM2.5 emissions at the end of different periods and the pollution pollutant concentration data at the beginning of the period, the contribution of PM2.5 emissions at different periods to the spatial separation index (E_p) can be calculated, and the calculation formula is as follows:

$$E_p = \frac{1}{2P_t} \sum_{i=1}^{n} \left| \frac{G_{it}}{G_i} P_t - P_{it} \right| - \frac{1}{2P_t} \sum_{i=1}^{n} \left| \frac{G_{it}}{G_t} P_t - P_{it} \right| \tag{5}$$

In the formula, t、t represents the end and beginning years of the research period respectively, and the meaning of other variables remains unchanged. If E_p is negative, it means that the change of PM2.5 emission makes the PM2.5 pollution and emission more matched in space, and the spatial separation is alleviated; If it is positive, the change of PM2.5 emission makes PM2.5 pollution and emission more separated in space, and the spatial separation phenomenon intensifies. Similarly, the contribution of PM2.5 concentration change to spatial separation index can be obtained. At present, most of the epidemiological studies of air pollution are based on Poisson regression proportional hazard model. Under this model, the population health effect value under a certain air pollutant concentration is:

$$E = E_0 \times \exp[\beta \times (C - C_0] \tag{6}$$

$$\begin{aligned} \varDelta E &= E_0 \times \{\exp[\beta \times (C - C_0)] - 1\} \\ &= E \times \{1 - 1/exp\ [\beta \times (C - C\_0\ )]\} \end{aligned} \tag{7}$$

Among them, β is the concentration death response parameter, that is, the percentage of health effect value change caused by the increase of unit concentration of pollutants, and five is the actual health effect value, which is the actual concentration of pollutants and the critical concentration of pollutants, and E_0 is the health effect value under the critical concentration of pollutants.

In addition, some research results choose the relative risk to express the exposure death response parameters, which can be used for health assessment according to the comprehensive effect value obtained by converting RR into β: $\beta = \mathrm{In}\ (RR)/\Delta C$ and then adding it to meta-analysis. In order to evaluate the impact of changes in PM2.5 on population health, assuming that the basic conditions of cities in 2017 and 2030, except for particulate pollution, population composition, medical conditions and other factors are consistent with those in 2012, equations (8) and (9) can be obtained.

$$E_2 = E_1 \times \exp[\beta \times (C_2 - C_1)] \tag{8}$$

$$\Delta E = E_1 = E_1 \times \exp[\beta \times (C_2 - C_1)] \times \left\{1 - \frac{1}{\exp[\beta \times (C_2 - C_0)]}\right\} \tag{9}$$

4. Result Analysis and Discussion

Through the observation and statistics of the training arrangement of nine small training cycles, it is shown that there are three types of small cycle arrangement of load structure during the study period, and the three small cycles are mainly arranged by one load rhythm (one medium load and one small load followed by one large load). Among them, the proportion of small cycles with large load, medium load and small load is the same, which is 33.3%.

As shown in Figure 4 and table 2.

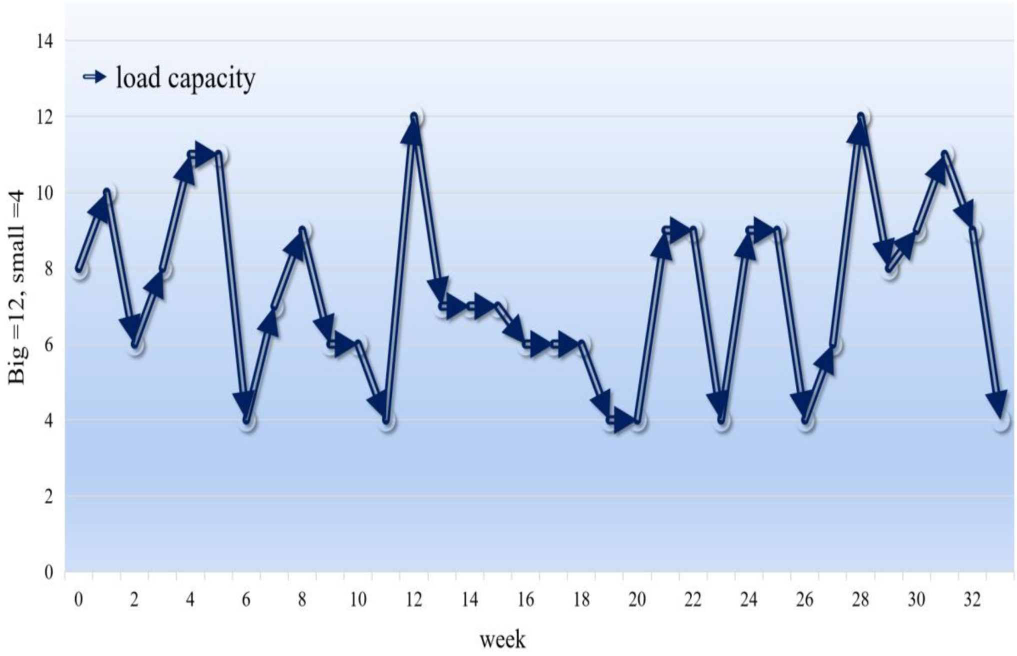


Figure 4: Rhythm arrangement of large cycle load during the study period

Table 2: Statistical table of large cycle load structure type and small cycle during the study period

TYPE	LARGE LOAD	MEDIUM LOAD	SMALL LOAD	TOTAL
SMALL PERIOD	3 Weeks	3 Weeks	3 Weeks	9 Weeks
PERCENTAGE	33.3%	33.3%	33.3%	100%

During the implementation of the training plan, the training content and load arrangement in different periods and stages were observed and analyzed. The sprinters of a university track and field team are trained in a small cycle of 6 days. According to the different levels of small cycle training load, it is divided into three types of load structure, and its arrangement rules are: large load small cycle arrangement of 3 classes of large load training, 2 classes of medium load training, 1 class of small load training; Medium load small cycle arrange 2 classes of high load training, 3 classes of medium load training, and 1 class of low load training; Small load and small cycle: 1 class of large load training, 3 classes of medium load training, and 2 classes of small load training.

Therefore, the arrangement characteristics of three load structure types with small cycles are presented. In different training stages, according to the needs of improving competitive ability, implement small cycles of different load content structure types. It can be seen from Figure 5 that the small cycle of medium load type is arranged for three weeks. The main load arrangement characteristics are that two large load training sessions are arranged every Wednesday and Saturday, three medium load training sessions are arranged on Monday, Tuesday and Friday, and one small load training session is arranged on Thursday.

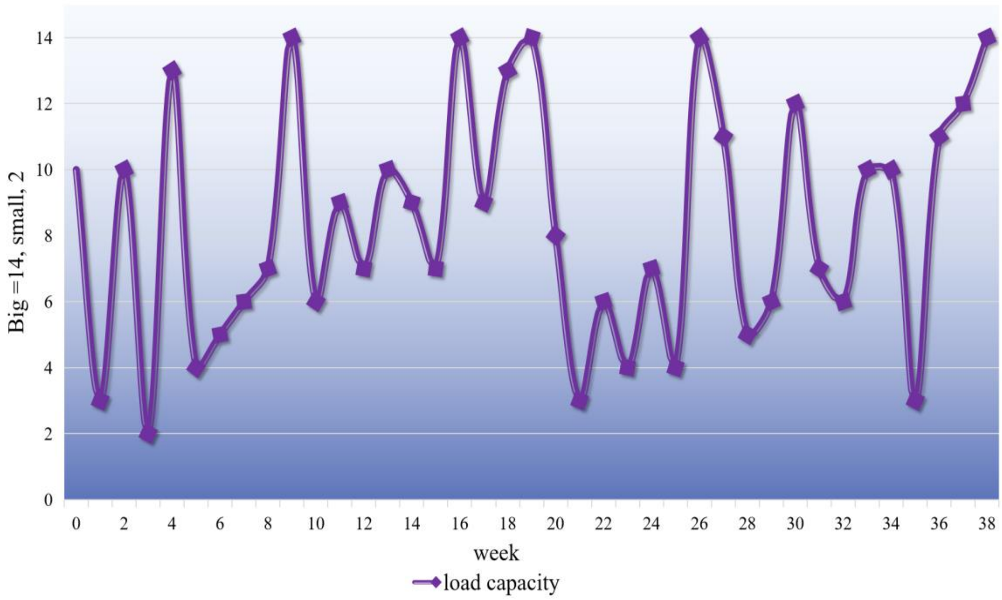
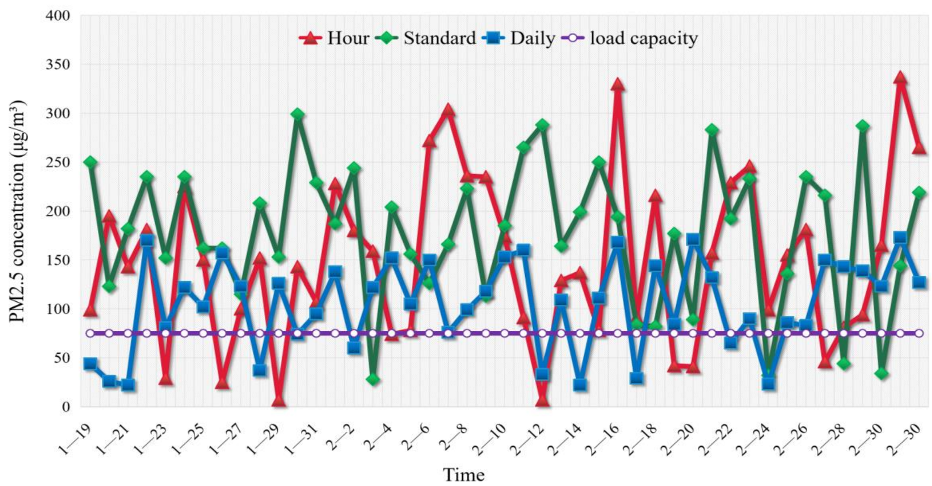
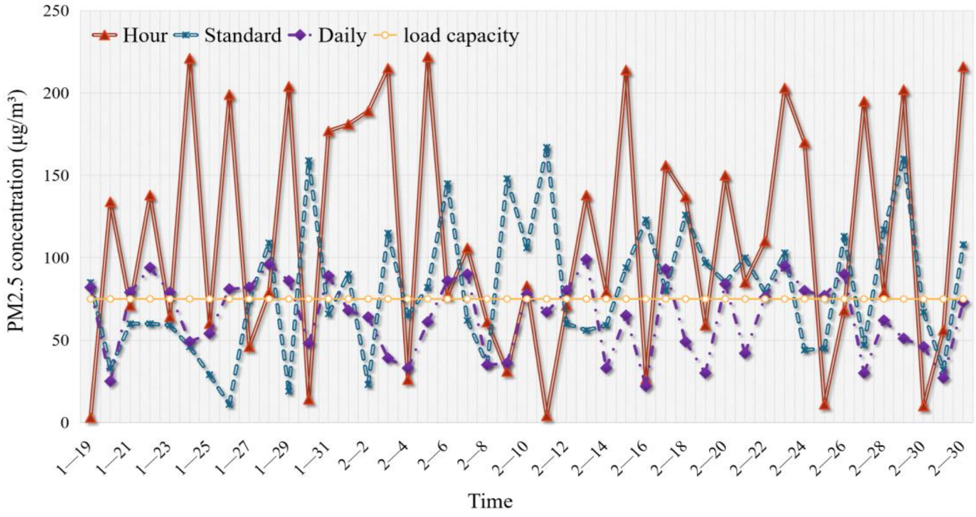


Figure 5: Characteristics of small cycle load arrangement of load type

During the continuous monitoring of athletes' PM2.5 exposure, the concentration of PM2.5 was higher in winter than in spring. During the winter monitoring period, the daily average mass concentration of PM2.5 exceeded the national standard limit (75.00μ g/m) to be implemented in 2016 for 10 days, while the remaining 10 days were lower than the standard value, with the average concentrations of (121.5 38.3) μ g/m and (50.1 22.3) μ g/m respectively; During the monitoring period in spring, the daily average mass concentration of PM2.5 exceeded the standard limit (75.00μ g/m) for 11 days, while the remaining 30 days were lower than the standard value, with the average concentrations of (88.9 9.3) μ g/m and (45 15.1) μ g/m, respectively. During the lung function test, the daily average mass concentration of PM2.5 exceeded 75.00μ g/m for 20 days, between 35.00) μ g/m and 75.00μ g/m for 17 days, and below 35.00μ g/m for 17 days. The days of heavy, medium and light load training were 18, 24 and 12 days, respectively. As shown in Figure 6.



(A)



(B)

Figure 6: PM2.5 hourly and daily average concentrations and daily load changes during the study period

According to the national standard limit of PM2.5 (35.00μ g/m, 75.00μ g/m) to be implemented in 2016, the daily average mass concentration of PM2.5 in the monitoring period is higher than 75.00μ g/m, and the average concentration is lower than 35.00μ g/m. In this paper, a soft-sensing model based on BP neural network is established. In order to test the generalization ability of the established model, that is, the ability to deal with unknown sample data to solve practical problems, another 100 groups of data are selected as the test sample set, and the established soft-sensing model is used to test the actual feasibility of the test sample set. Fig. 7 is the fitting curve of the model output result and the target output result of the training sample set. It can be seen from fig. 7 that the fitting effect of the model output curve and the target output curve is good, and the mean square error of the two is 2.9718×10-5.

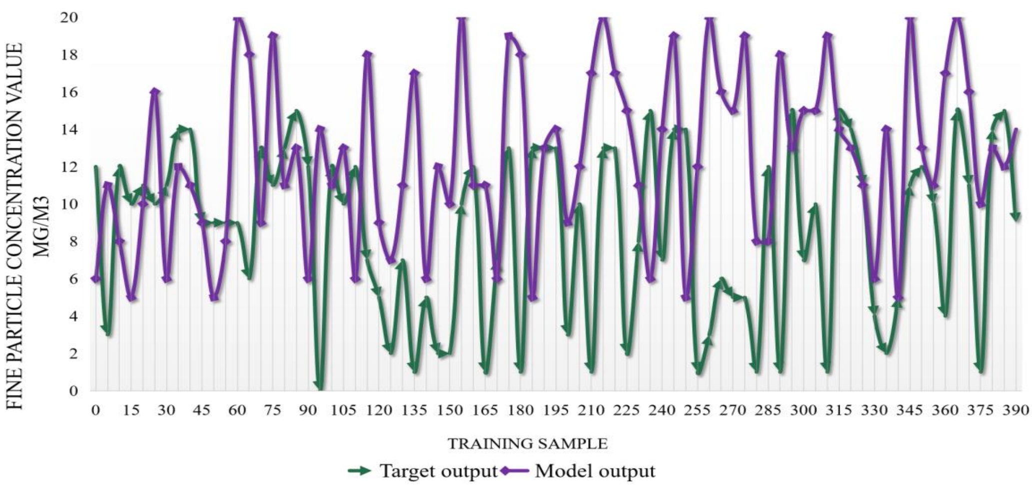


Figure 7: Fitting curve between model output and target output of BP network model training sample set

The trained BP network model is applied to the soft measurement experiment of the test sample set. The BP network model fits the curve between the soft measurement value of the test sample set and the actual value. It can be seen that the soft measurement value curve of the test sample set fits well with the actual value curve, the trend of the curve is basically the same, and there is no excessive deviation at 100 sample points. After calculation, the mean square error of the soft measurement result is 3.9806 × 10-4, the average absolute error is 0.0174, and the average relative error is 22%. BP network model is a soft measurement model based on neural network, which takes six screened influence factors such as SO2 concentration, NO2 concentration, PM10 concentration, air pressure, relative humidity and wind speed as the input vector of the network model, and the corresponding fine particle concentration as the output vector of the network model.

The modeling process of BP network model is complex, and there are many parameters to be set. The mean square error of the soft measurement results of the test sample set is 3.9806 × 10-4, the average absolute error is 0.0174, the average relative error is 22%, the linear correlation coefficient is 0.9457, the average accuracy is 78%, and the accuracy score is 81. When constructing the network model, the parameters of the BP network model are determined by comparing the running results of the model through empirical method and heuristic method, and the model with the best comprehensive performance is constructed.

After that, the established model is tested, and the test results show that the average accuracy and accuracy score of BP network model can meet the needs of soft-sensing work. Finally, for the convenience of users, the system interface written by MATLAB GUI can make soft measurement and result analysis of fine particle concentration simply and quickly. In different time scales, PCA is applied to analyze the monitoring sample data of atmospheric particulate pollutants at various monitoring points in a city. Before PCA analysis, the corresponding analysis of eliminating trends is carried out. DCA results show that the maximum values of the first two axes in the daily time scale are all less than 2 units, which indicates that the monitoring samples of PM10 and PM2.5 in each monitoring point meet the precondition of PCA analysis in the daily time scale.

From Table 3, it can be seen that the cumulative percentage of variance of the first two axes of the monitoring samples of atmospheric particulate pollutants in a city at different time scales is about 90%, that is, the first two principal components have summarized most of the information covered by each influencing variable. The cumulative capture variance of the first two axes of PM10 is 88.9%, and the cumulative capture variance of the first two axes of PM2.5 is 90.2%.

Table 3: Statistical characteristics of the first three axes of the principal component analysis of the daily characteristics of atmospheric particulate pollutants in a city

TIME SCALE	CONTAMINANTS	PARAMETER	PC1	PC2	PC3
SEASON	PM10	Characteristic value	2.4512	0.4563	0.3132
		Cumulative percentage of variance%	0.7452	0.1562	100
	PM2.5	characteristic value	2.2464	0.1524	0.2541
		Cumulative percentage of variance%	0.7625	0.9134	100

PCA analysis of PM10 and PM2.5 on the time scale of days reveals that there are relatively large differences in the daily time segments that affect the concentration changes of PM10 and PM2.5.

5. Conclusions

The pollution concentration of fine particles in the atmosphere is affected by atmospheric diffusion and dilution ability. The smaller the particle size, the more toxic substances it carries, and the greater the damage to human body's motor function. The mass concentration of atmospheric particulate matter in winter and spring is obviously higher than that in summer and autumn, and the peak of coarse particles TSP and PM10 appears in spring, while the peak of fine particles PM2.5 and PM1.0 appears in winter. The annual changes of coarse particles TSP and PM10 show a bimodal curve, while fine particles PM2.5 and PM10 show a "U" curve. The experimental results of the influence on the free radical content of high-intensity exercise human body show that the pollution of atmospheric fine particles will reduce the data of high-intensity exercise human body, such as serum MDA, serum reactive oxygen species, lung MDA, BALF reactive oxygen species, lung MDA, BALF reactive oxygen species, heart MDA, heart reactive oxygen species, liver MDA, liver reactive oxygen species, quadriceps femoris, quadriceps femoris reactive oxygen species and so on, That is, the pollution of fine particles in the atmosphere will reduce the free radical content of high-intensity exercise human body. This paper proves the feasibility of establishing a soft sensing model based on neural network to monitor the concentration of fine particles in the atmosphere through the experiment of establishing a soft sensing model.

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