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Working Paper

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Tinbergen Institute Discussion Paper, No. 16-027/III

Provided in Cooperation with:
Tinbergen Institute, Amsterdam and Rotterdam

Suggested Citation: Yue, Xiao-Guang; Gao, Rui; McAleer, Michael (2016) : Prediction of Gas Concentration based on the Opposite Degree Algorithm, Tinbergen Institute Discussion Paper, No. 16-027/III, Tinbergen Institute, Amsterdam and Rotterdam

This Version is available at:
https://hdl.handle.net/10419/145334

TI 2016-027/III
Tinbergen Institute Discussion Paper

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April 2016

* For financial support, the first two authors acknowledge the financial support of the National Natural Science Foundation of China (NSFC) (No. 51178358), and the third author wishes to acknowledge the Australian Research Council and the National Science Council, Taiwan.

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Abstract

In order to study the dynamic changes in gas concentration, to reduce gas hazards, and to protect and improve mining safety, a new method is proposed to predict gas concentration. The method is based on the opposite degree algorithm. Priori and posteriori values, opposite degree computation, opposite space, prior matrix, and posterior matrix are 6 basic concepts of opposite degree algorithm. Several opposite degree numerical formulae to calculate the opposite degrees between gas concentration data and gas concentration data trends can be used to predict empirical results. The opposite degree numerical computation (OD-NC) algorithm has greater accuracy than several common prediction methods, such as RBF (Radial Basis Function) and GRNN (General Regression Neural Network). The prediction mean relative errors of RBF, GRNN and OD-NC are 7.812%, 5.674% and 3.284%, respectively. Simulation experiments shows that the OD-NC algorithm is feasible and effective.

Keywords: Gas concentration, opposite degree algorithm, data prediction, mining safety, numerical simulations.

JEL: C53, C63, L71.

1 Introduction

Mine gases can result in hypoxia, asphyxia, or even burning and explosions, so it is an important indicator to detect gas concentration for coal mine gas safety. Gas concentration must be maintained at a reasonable level as it indicates that the coal mine is safe. In China, for example, gas concentration security issues lead to many casualties each year, as shown in Table 1 (see [1]). For available data from 2008 to 2012, total Chinese coal mine gas accidents totalled 675, which led to 3039 deaths.

Table 1

Annual coal mine gas accidents statistics for 2008-2012

Year	2008	2009	2010	2011	2012	Total Number
Accidents Times	182	157	145	119	72	675
Number of Deaths	778	755	623	553	459	3039

At the international level, prediction of gas concentration is also a serious issue, so it is not surprising that significant research has been conducted to predict gas concentration. Fang [2] used numerical methods to predict gas concentration in 1993. Zhou [3] established the gas concentration fuzzy time series forecasting model in 1995, and applied the model to the Sichuan Furong Mining Bureau Baijiao Mine. The model to prevent gas explosion accidents was subsequently used to predict gas concentration [3].

In 2008, Obst et al. [4] used echoes to monitor coal mine gas concentration, while Sikora et al. [5] presented mixed adaptive system prediction method of time series continuous gas monitoring. In 2010, Wei et al. [6] analyzed forecasting methods based on the gas concentration HJM model and Monte Carlo simulation methods.

Wang et al. [7] analyzed the gas concentration prediction methods based on

transformed wavelet and optimized predictor in 2011. Unnikrishna Menon at al. [8] argued in 2012 that gas concentration and prominent detection security is important for the protection of mine workers and areas close to the mines, and designed gas wireless sensor networks (WSN), where the semiconductor gas sensor had a low power consumption and high sensitivity. Optimizing power is based on energy efficient clustering protocols, so that the goal of outburst warning can be achieved [8].

Intelligent methods in the prediction of gas emission rates and concentration are increasing, including neural networks and genetic algorithms. These methods have certain advantages and disadvantages. For example, neural networks require a large amount of data and are prone to the “less learning” and “over-learning” phenomena, leading to the prediction accuracy that is not high. BP neural network will be affected by the network structure, with initial connection weights and thresholds set for training [9].

Genetic algorithms use selecting, crossover and mutation operations for computation. It has a strong global processing capacity, but local processing capacity can be weak [10]. Therefore, in order to further improving forecast accuracy and the adaptability of the algorithm, in this paper we propose a new intelligent algorithm which can be applied to the prediction of mine gas concentration.

2. Basic Concepts of the Opposite Degree Algorithm

Gas data are dynamic, and the gas relationship with available data can be represented by the Opposite Degree (OD). The greater is the opposite degree, the greater are the differences between two associated variables; the smaller is the opposite degree, the smaller are the differences between two associated variables. The opposite degrees are predominantly related with the following six concepts [11-14].

1) a priori value

Priori value refers to the data that have been used for training, and hence are obtained in advance.

2) a posteriori value

Posteriori analysis is used to predict the value. Posteriori value is the value associated with a certain set of properties.

3) opposite degree computation

Opposite degree is the difference between the a priori and a posteriori values, and range from $(-\infty, +\infty)$.

Usually, the a priori value is *A*, the a posteriori value is *B*, denoted as *O(A,B)*, and can be obtained using formula (1), as follows:

$$O(A,B) = \frac{B-A}{A} = \begin{cases} negative, \ for \ B < A \\ 0 \ for \ A = B \\ positive \ for \ B > A \end{cases} \tag{1}$$

4) opposite space

Flat space and three-dimensional space are the most common vector spaces. The flat space is the vector space R^2, which consists of the real pairs:

$$R^2 = \{(x, y) : x, y \in R\}. \tag{2}$$

The vector space R^3 is three-dimensional space, which consists of all ordered triple real arrays:

$$R^3 = \{(x, y, z) : x, y, z \in R\}. \tag{3}$$

The concept of R^2 and R^3 can be extended to high-dimensional space. Setting the length as *n*, an ordered array (Vector space R^n) is given in formula (4):

$$R^n = \{(x_1, x_2, ..., x_n) : x_1, x_2, ..., x_n \in R\} \tag{4}$$

where $j \in \{1, 2, ..., n\}$.

In the multi-dimensional space, the calculation of the opposite degree is changed to the vector calculation. The a priori value is changed to the a priori vector, $A = (A_1, A_2, ..., A_m)$, while the a posteriori value changed to the a posteriori vector, $B = (B_1, B_2, ..., B_m)$. The calculations are shown in formulae (5) and (6):

$$O(A, B) = \{O_1(A_1, B_1), O_2(A_2, B_2), ..., O_m(A_m, B_m)\} \tag{5}$$

$$O(A, B) = \begin{pmatrix} O_1(A_1, B_1) \\ O_2(A_2, B_2) \\ ... \\ O_m(A_m, B_m) \end{pmatrix} \tag{6}$$

5) a priori matrix

The a priori matrix is a matrix (data set) that is used to train the prediction method. The a priori matrices are obtained in advance of the numerical matrix, consisting of the a priori numerical composition, a_{ij} ($a_{ij} \in A_{m \times n}$, $1 \le i \le m$, $1 \le j \le n$). They include the n column properties, with each column having m row data, and each row of data corresponding to the a priori values, r_i ($r_i \in R$, $1 \le i \le m$).

The given prior matrix $A_{m \times n}$ is shown in formula (7):

$$A_{m\times n}=\begin{bmatrix} a_{11} & a_{12} & \ldots & a_{1n} \\ a_{21} & a_{22} & \ldots & a_{2n} \\ \ldots & \ldots & \ldots & \ldots \\ a_{m1} & a_{m2} & \ldots & a_{mn} \end{bmatrix} \tag{7}$$

where it's a priori numerical column vector is R.

$$R=\begin{bmatrix} r_1 \\ r_2 \\ \ldots \\ r_m \end{bmatrix} \tag{8}$$

6) a posteriori matrix

The a posteriori matrix refers to a matrix (data set) that has been used for predictive analysis. The a posteriori matrix is composed of the value of the a posteriori b_{kj} ($b_{kj} \in B_{p\times n}$, $1\le k\le p$, $1\le j\le n$), including n column properties, with each column property having p rows of data, and each row corresponding to the a posterior value, s_k ($s_k \in S$, $1\le k\le p$). Opposite degree calculations require the a posteriori predicted values.

The given a posteriori matrix, $B_{p\times n}$, is shown in formula (9):

$$B_{p\times n}=\begin{bmatrix} b_{11} & b_{12} & \ldots & b_{1n} \\ b_{21} & b_{22} & \ldots & b_{2n} \\ \ldots & \ldots & \ldots & \ldots \\ b_{p1} & b_{p2} & \ldots & b_{pn} \end{bmatrix} \tag{9}$$

The opposite degree algorithm can be used to predict the value of the a posteriori matrix, $B_{p\times n}$, corresponding to the column vector S:

$$S = \begin{bmatrix} s_1 \\ s_2 \\ \cdots \\ s_m \end{bmatrix} \tag{10}$$

3. Opposite Degree Algorithm - Numerical Computation

As there can be many non-linear relationships, how to calculate the distance between these values is very important. We could consider using the method of numerical calculation of the opposite degree algorithm. The smaller is opposite degree between two gas emission quantities, the closer they will be; when two gas emission opposite degrees are greater, the further apart will the difference be between them. Similarly, the smaller are the opposite degree related indicators between two sets of gas emission data, the closer they will be; the greater are the opposite degree related indicators between two sets of gas emission data, the greater will be the difference.

Due to the opposite degree vector being constructed by opposite degree components, the opposite degree space is constituted by opposite degree vectors. Therefore, the calculations of the opposite degrees is clearly closed, resulting in the collection of the operation as the opposite degree space. The main steps of the opposite degree numerical computation algorithm can be summarized in the following four steps:

1) Establish populations of neural networks, and compute the basic characteristics of the a priori values. Calculating the value of the basic characteristics of the a priori initial opposite degree of the individual data, from the population correlation network, will facilitate calculation of the weights.

2) Assess the fitness by calculating the weights, which are used to give the “individual data items / indicators” relative importance, and then select the value of the a posteriori values.

3) Select high fitness data. The opposite degree algorithm performed the

calculations, and the comparisons based on weights and various parameters.

4) According to the parameters calculated, predict the a posteriori values.

As a result, the opposite degree numerical computation (OD-NC) method can be used based on matrix operations. The OD-NC steps are shown as follows:

1) Calculate the opposite degree matrix of the training sample. The opposite degree matrix, $O_i(1 \le i \le m)$, is the opposite degree between the ith row of $A_{m\times n}R$ and the mth row of $A_{m\times n}R$, where $A_{m\times n}R$ is composed of matrix $A_{m\times n}$ and vector R, with m rows and $n+1$ columns. The calculation of the matrix of opposite degrees is shown in formulae (11) and (12):

$$O_i = \begin{bmatrix} O(a_{11},a_{i1}) & O(a_{12},a_{i2}) & \dots & O(a_{1n},a_{in}) & O(r_1,r_i) \\ O(a_{21},a_{i1}) & O(a_{22},a_{i2}) & \dots & O(a_{2n},a_{in}) & O(r_2,r_i) \\ \dots & \dots & \dots & \dots & \dots \\ O(a_{m1},a_{i1}) & O(a_{m2},a_{i2}) & \dots & O(a_{mn},a_{in}) & O(r_m,r_i) \end{bmatrix} \tag{11}$$

$$O_i = \begin{bmatrix} \frac{a_{i1}-a_{11}}{a_{11}} & \frac{a_{i2}-a_{12}}{a_{12}} & \dots & \frac{a_{in}-a_{1n}}{a_{1n}} & \frac{r_i-r_1}{r_1} \\ \frac{a_{i1}-a_{21}}{a_{21}} & \frac{a_{i2}-a_{22}}{a_{22}} & \dots & \frac{a_{in}-a_{2n}}{a_{2n}} & \frac{r_i-r_2}{r_2} \\ \dots & \dots & \dots & \dots & \dots \\ \frac{a_{i1}-a_{m1}}{a_{m1}} & \frac{a_{i2}-a_{m2}}{a_{m2}} & \dots & \frac{a_{in}-a_{mn}}{a_{mn}} & \frac{r_i-r_m}{r_m} \end{bmatrix} \tag{12}$$

2) Calculate weights, where ω_j represents the weight of each data (a_{ij}), and is based on the following steps:

(1) Remove all the 0 rows from matrix O_i, which gives O_i', as all the 0 rows cannot be used to compute the weights. There are i matrices, which can be composed of matrix O', as shown in formula (13):

$$O' = \begin{bmatrix} O'_1 \\ O'_2 \\ \dots \\ O'_m \end{bmatrix} = \begin{bmatrix} O(a_{21}, a_{11}) & O(a_{22}, a_{12}) & \dots & O(a_{2n}, a_{1n}) & O(r_2, r_1) \\ O(a_{31}, a_{11}) & O(a_{32}, a_{12}) & \dots & O(a_{3n}, a_{1n}) & O(r_3, r_1) \\ \dots & \dots & \dots & \dots & \dots \\ O(a_{m1}, a_{11}) & O(a_{m2}, a_{12}) & \dots & O(a_{mn}, a_{1n}) & O(r_m, r_1) \\ O(a_{11}, a_{21}) & O(a_{12}, a_{22}) & \dots & O(a_{1n}, a_{2n}) & O(r_1, r_2) \\ O(a_{31}, a_{21}) & O(a_{32}, a_{22}) & \dots & O(a_{3n}, a_{2n}) & O(r_3, r_2) \\ \dots & \dots & \dots & \dots & \dots \\ O(a_{m1}, a_{21}) & O(a_{m2}, a_{22}) & \dots & O(a_{mn}, a_{2n}) & O(r_m, r_2) \\ \dots & \dots & \dots & \dots & \dots \\ O(a_{11}, a_{m1}) & O(a_{12}, a_{m2}) & \dots & O(a_{1n}, a_{mn}) & O(r_1, r_m) \\ O(a_{21}, a_{m1}) & O(a_{22}, a_{m2}) & \dots & O(a_{2n}, a_{mn}) & O(r_2, r_m) \\ \dots & \dots & \dots & \dots & \dots \\ O(a_{m-1,1}, a_{m1}) & O(a_{m-1,2}, a_{m2}) & \dots & O(a_{m-1,n}, a_{mn}) & O(r_{m-1}, r_m) \end{bmatrix} \quad (13)$$

(2) The last column is a reference value for prediction, namely O''. The calculation of the matrix of the weights is given in formula (14):

$$O'' = \begin{bmatrix} O''_1 \\ O''_2 \\ \dots \\ O''_m \end{bmatrix} =$$

$$\begin{bmatrix} O(O(r_2, r_1), O(a_{21}, a_{11})) & O(O(r_2, r_1), O(a_{22}, a_{12})) & \dots & O(O(r_2, r_1), O(a_{2n}, a_{1n})) \\ O(O(r_3, r_1), O(a_{31}, a_{11})) & O(O(r_3, r_1), O(a_{32}, a_{12})) & \dots & O(O(r_3, r_1), O(a_{3n}, a_{1n})) \\ \dots & \dots & \dots & \dots \\ O(O(r_m, r_1), O(a_{m1}, a_{11})) & O(O(r_m, r_1), O(a_{m2}, a_{12})) & \dots & O(O(r_m, r_1), O(a_{mn}, a_{1n})) \\ O(O(r_1, r_2), O(a_{11}, a_{21})) & O(O(r_1, r_2), O(a_{12}, a_{22})) & \dots & O(O(r_1, r_2), O(a_{1n}, a_{2n})) \\ O(O(r_3, r_2), O(a_{31}, a_{21})) & O(O(r_3, r_2), O(a_{32}, a_{22})) & \dots & O(O(r_3, r_2), O(a_{3n}, a_{2n})) \\ \dots & \dots & \dots & \dots \\ O(O(r_m, r_2), O(a_{m1}, a_{21})) & O(O(r_m, r_2), O(a_{m2}, a_{22})) & \dots & O(O(r_m, r_2), O(a_{mn}, a_{2n})) \\ \dots & \dots & \dots & \dots \\ O(O(r_1, r_m), O(a_{11}, a_{m1})) & O(O(r_1, r_m), O(a_{12}, a_{m2})) & \dots & O(O(r_1, r_m), O(a_{1n}, a_{mn})) \\ O(O(r_2, r_m), O(a_{21}, a_{m1})) & O(O(r_2, r_m), O(a_{22}, a_{m2})) & \dots & O(O(r_2, r_m), O(a_{2n}, a_{mn})) \\ \dots & \dots & \dots & \dots \\ O(O(r_{m-1}, r_m), O(a_{m-1,1}, a_{m1})) & O(O(r_{m-1}, r_m), O(a_{m-1,2}, a_{m2})) & \dots & O(O(r_{m-1}, r_m), O(a_{m-1,n}, a_{mn})) \end{bmatrix} \quad (14)$$

(3) Calculate absolute values, where the weights denote the important levels:

$$|O''|=\begin{bmatrix}|O_1''|\\|O_2''|\\...\\|O_m''|\end{bmatrix} \tag{15}$$

(4) Calculate the mean value of each column. Prior to any calculations, part of the column may contain “E”, in which case the results of the "E" are deleted from the data, and calculate the mean value, with $\overline{\omega_i}$ taken as the mean value for each column. The default value of the “E” is 0. The calculations are shown in formula (16):

$$\overline{\omega_i}=\frac{\sum(|O(O(r_2,r_1),O(a_{2i},a_{1i}))|+|O(O(r_3,r_1),O(a_{3i},a_{1i}))|+...+|O(O(r_{m-1},r_m),O(a_{m-1,i},a_{mi}))|)}{m\cdot(m-1)} \tag{16}$$

(5) Calculate the weight. First, calculate the reciprocal of the mean value; second, obtain the sum; and finally, divide the total weight by the sum. The weight for each column is ω_j, and the calculation is shown in formula (17):

$$\omega_i=\frac{\frac{1}{\overline{\omega_i}}}{\frac{1}{\overline{\omega_1}}+\frac{1}{\overline{\omega_2}}+...+\frac{1}{\overline{\omega_n}}} \tag{17}$$

3) Calculate the prediction sample opposite degree matrix**.** $\hat{O}_k$ is the opposite degree matrix based on the opposite degree calculation of row k $(1\le k\le p)$ of $B_{p\times n}$ and row m of $A_{m\times n}$, as given below

$$\hat{O}_k = \begin{bmatrix} O(a_{11},b_{k1}) & O(a_{12},b_{k2}) & ... & O(a_{1n},b_{kn}) \\ O(a_{21},b_{k1}) & O(a_{22},b_{k2}) & ... & O(a_{2n},b_{kn}) \\ ... & ... & ... & ... \\ O(a_{m1},b_{k1}) & O(a_{m2},b_{k2}) & ... & O(a_{mn},b_{kn}) \end{bmatrix}$$
$$= \begin{bmatrix} \frac{b_{k1}-a_{11}}{a_{11}} & \frac{b_{k2}-a_{12}}{a_{12}} & ... & \frac{b_{kn}-a_{1n}}{a_{1n}} \\ \frac{b_{k1}-a_{21}}{a_{21}} & \frac{b_{k2}-a_{22}}{a_{22}} & ... & \frac{b_{kn}-a_{2n}}{a_{2n}} \\ ... & ... & ... & ... \\ \frac{b_{k1}-a_{m1}}{a_{m1}} & \frac{b_{k2}-a_{m2}}{a_{m2}} & ... & \frac{b_{kn}-a_{mn}}{a_{mn}} \end{bmatrix} \quad (18)$$

4) Calculate the test sample's mean opposite degree and weighted opposite degree. The calculation methods of the mean opposite degree, ξ_{kj} ($1 \le i \le m$, $1 \le k \le p$, $1 \le j \le m$), and the weighted opposite degree, $\hat{\xi}_{kj}$ ($1 \le i \le m$, $1 \le k \le p$, $1 \le j \le m$), are given in formulae (19) and (20), respectively:

$$\xi_{kj} = \frac{\sum (O(a_{i1},b_k) + O(a_{i2},b_{k2}) + ... + O(a_{in},b_{kn}))}{n} \quad (19)$$

$$\hat{\xi}_{kj} = \sum (O(a_{i1},b_{k1}) \cdot \omega_1 + O(a_{i2},b_{k2}) \cdot \omega_2 + ... + O(a_{in},b_{kn}) \cdot \omega_n) \quad (20)$$

5) Calculate alternative data row. According to formula (21), select the rows that contain β_{kl} ($1 \le k \le p$, $1 \le l \le n$) as the alternative row:

$$\beta_{kl} = \min(|O(a_{1n},b_{kn})|, |O(a_{2n},b_{kn})|, ..., |O(a_{mn},b_{kn})|) . \quad (21)$$

6) Find the basis data row. Select the row with minimum value ($\min(\xi_{kj})$), and record its real value as s_k.

7) Calculate the result matrix based on formula (22):

$$\hat{s}_k = s_k \times (1 + \hat{\xi}_{kj}), \tag{22}$$

where the output is the result matrix:

$$\hat{S} = \begin{bmatrix} \hat{s}_1 \\ \hat{s}_2 \\ \cdots \\ \hat{s}_p \end{bmatrix} \tag{23}$$

4. Gas Concentration Analysis and Prediction Based on OD-NC

4.1 Data sources

We select several commonly used variables in the analysis of gas concentration: wind speed (*m/s*), temperature (℃), negative pressure (*kpa*), CO concentration (*ppm*), and 3 minutes for the interval form time series, as shown in Table 2 [15].

The following are used to identify the variables, where G_1, F_1, F_2, F_3, F_4 are wind speed (*m/s*), temperature (℃), negative pressure (*kpa*), and CO concentration (*ppm*), respectively.

Table 2

Gas concentration data

Time (min)	G_1	F_1	F_2	F_3	F_4
0:00	0.95	1.8	9.25	0.61	3.5
0:03	0.93	1.88	9.25	0.61	3
0:06	0.94	1.58	9.25	0.61	3
0:09	0.93	1.8	9.25	0.61	3
0:12	0.93	1.67	9.31	0.61	3
0:15	0.98	1.67	9.31	0.62	3

0:18	0.95	1.8	9.31	0.61	3
0:21	0.95	1.8	9.31	0.61	3
0:24	0.95	1.89	9.31	0.61	3
0:27	0.94	1.88	9.31	0.61	2
0:30	0.94	1.89	9.31	0.61	2
0:33	0.93	1.8	9.31	0.61	2
0:36	0.95	1.8	9.31	0.61	2.5
0:39	0.95	1.67	9.31	0.61	3
0:42	0.93	1.99	9.31	0.61	3
0:45	0.94	1.89	9.31	0.61	3
0:48	0.98	1.88	9.31	0.61	12
0:51	1.02	1.78	9.31	0.61	18.75
0:54	1.05	1.67	9.38	0.61	20.75
0:57	1.01	1.89	9.38	0.61	17.75
1:00	1	1.89	9.38	0.61	7.5
1:03	0.98	1.67	9.38	0.61	5
1:06	0.95	1.88	9.38	0.61	4.5
1:09	0.95	2.08	9.38	0.61	3.5
1:12	0.98	1.99	9.38	0.61	3.5
1:15	0.95	1.78	9.38	0.6	3.5
1:18	0.95	1.78	9.38	0.6	3.5
1:21	0.98	1.89	9.38	0.61	3.5
1:24	0.98	1.67	9.31	0.6	3
1:27	0.98	1.99	9.31	0.6	3

The time series is not included in the calculations, and the final gas concentration data are shown in Table 3. In the comparisons, we select the top 22 groups as training samples, and the last 8 groups as test samples.

Table 3

Final gas concentration data

No.	F_1	F_2	F_3	F_4	G_1
1	1.8	9.25	0.61	3.5	0.95
2	1.88	9.25	0.61	3	0.93
3	1.58	9.25	0.61	3	0.94
4	1.8	9.25	0.61	3	0.93
5	1.67	9.31	0.61	3	0.93
6	1.67	9.31	0.62	3	0.98
7	1.8	9.31	0.61	3	0.95
8	1.8	9.31	0.61	3	0.95
9	1.89	9.31	0.61	3	0.95
10	1.88	9.31	0.61	2	0.94
11	1.89	9.31	0.61	2	0.94
12	1.8	9.31	0.61	2	0.93
13	1.8	9.31	0.61	2.5	0.95
14	1.67	9.31	0.61	3	0.95
15	1.99	9.31	0.61	3	0.93
16	1.89	9.31	0.61	3	0.94
17	1.88	9.31	0.61	12	0.98
18	1.78	9.31	0.61	18.75	1.02
19	1.67	9.38	0.61	20.75	1.05
20	1.89	9.38	0.61	17.75	1.01
21	1.89	9.38	0.61	7.5	1
22	1.67	9.38	0.61	5	0.98
23	1.88	9.38	0.61	4.5	0.95
24	2.08	9.38	0.61	3.5	0.95
25	1.99	9.38	0.61	3.5	0.98

26	1.78	9.38	0.6	3.5	0.95
27	1.78	9.38	0.6	3.5	0.95
28	1.89	9.38	0.61	3.5	0.98
29	1.67	9.31	0.6	3	0.98
30	1.99	9.31	0.6	3	0.98

4.2 Gas concentration prediction based on OD-NC

The calculation procedure is based on the OD-NC algorithm. The prediction results are given in formula (24):

$$\hat{S} = \begin{bmatrix} 0.9671 \\ 0.9096 \\ 0.8966 \\ 0.9449 \\ 0.9449 \\ 0.9628 \\ 0.9464 \\ 0.9265 \end{bmatrix} \tag{24}$$

4.3 Gas concentration analysis based on OD-NC

In order to analyze the accuracy of the OD-NC algorithm, we provide a comparative analysis of the RBF, GRNN and OD-NC algorithms. The RBF (Radial Basis Function) is a radial basis function neural network, and the GRNN (General Regression Neural Network) algorithm is a generalized regression neural network.

These three algorithms are designed for processing the data in Table 3. For purposes of comparison with the real values, the three methods are used to predict the real values in Table 4 and Figure 1, to predict the relative errors of the results in Table 5, and to predict the mean relative errors of the results in Table 6.

Table 4

Prediction results

No.	Real Value (%)	Prediction Value (%)		
		OD-NC	*RBF*	*GRNN*
1	0.95	0.9671	0.7791	0.9574
2	0.95	0.9096	0.8571	0.8089
3	0.98	0.8966	0.8919	0.8897
4	0.95	0.9449	0.9274	0.9528
5	0.95	0.9449	0.9274	0.9528
6	0.98	0.9628	0.9229	0.9540
7	0.98	0.9464	0.8998	0.8994
8	0.98	0.9265	0.9117	0.8910

Table 5

Relative errors of the three methods

No.	Relative Error (%)		
	OD-NC	*RBF*	*GRNN*
1	0.0180	0.1799	0.0078
2	0.0425	0.0978	0.1485
3	0.0851	0.0899	0.0921
4	0.0054	0.0238	0.0029
5	0.0054	0.0238	0.0029
6	0.0176	0.0583	0.0265
7	0.0343	0.0818	0.0822
8	0.0546	0.0697	0.0908

Table 6

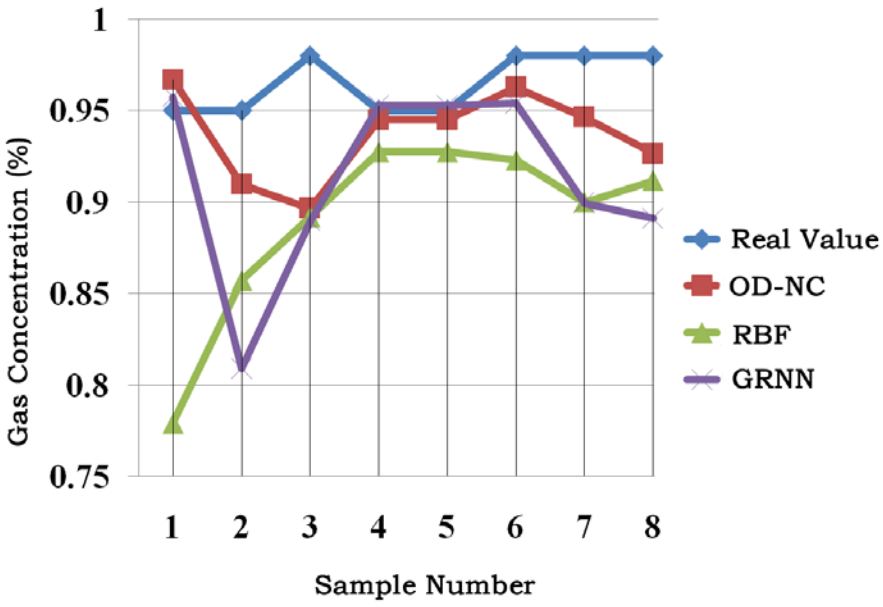
Mean relative errors of the three methods

Method	*OD-NC*	*RBF*	*GRNN*
Mean Relative Error (%)	3.2837	7.8120	5.6736

From the above tables, the relative error and mean relative error are compared. The OD-NC algorithm is superior to the RBF and GRNN algorithms. From Figure 1, it is intuitive to see the prediction results of the different methods, which shows that the real value is close to the OD-NC prediction results. In Table 6, the OD-NC relative error control in less than 4%. Therefore, the OD-NC algorithm is a feasible and effective method for predicting gas concentration.

Figure 1

Prediction results



4. Concluding Remarks

The paper introduced the concept of opposites, constructed opposite degree algorithm, and discussed the OD-NC algorithm principle, as follows: (1) the opposite degree algorithm was obtained by cyclic matrix and data, and by expressing the relationship of the training data; (2) calculated the effect of data and matrix of the predicted value, obtained the degree of opposition, and then analyzed the influencing factors of weight; (3) according to the weight values and testing data of opposite degree mean and the weighted opposite degree, determined the reference for calculation; and (4) through the opposite degree algorithm, calculated numerical data can be predicted.

The prediction results showed that: (1) the OD-NC algorithm was superior to the competing RBF and GRNN algorithms; and (2) the mean error of the OD-NC algorithm was controlled within 4%, which was lower than for the other methods. Therefore, the OD-NC algorithm was feasible and effective in the prediction and analysis of gas concentration.

Conflict of interest

The authors confirm that the article content has no conflict of interest.

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