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# Improved Algorithm of Intelligent Decision Making for Precise Application of Nitrogen Fertilizer to Melon Based on Artificial Intelligence

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**Abstract.** As agriculture enters the 4.0 era, the demand for intelligent and precise agricultural production is gradually increasing. However, the high cost of agricultural data collection, insufficient decision-making models and low level of intelligence are still the main obstacles to the improvement of land output rate and labor productivity in the process of agricultural production. In this paper, to address the long-standing problems of high cost of soil nitrogen content sampling, difficulty in acquiring soil nitrogen content and reduced accuracy of model long-term prediction during melon growth, a soil nitrogen content prediction model based on improved BP neural network combining a small amount of sampling and a comprehensive model is constructed to realize intelligent decision making of melon nitrogen fertilizer application.

**Keywords:** neural network algorithm, nitrogen content, intelligent decision

## 1 Introduction

In China, when and how much chemical fertilizer is applied depends on the experience of the applicator. Unscientific fertilization is widespread, especially in areas with underdeveloped science and technology, such as rural areas. Improper use of chemical fertilizer will cause great pollution to land quality and the environment [1]. This will not only lead to the reduction of crop yield and land quality, but also bring unnecessary economic losses and burdens to the majority of farmers. Nitrogen is the main fertilizer element in the growth process of melon and plays an important role in the whole growth cycle [2]. The increase of nitrogen content in melon plants can promote fruit expansion, increase the weight of single fruit and improve the appearance of fruit, and at the same time, the absorption of nitrogen, phosphorus and potassium by melon plants under different conditions of nitrogen level also shows different effects [3]. Many scholars have done related work on the fertilization amount prediction algorithm, but the problems of the current algorithm mainly focus on the following two aspects: Firstly, relying on a large number of soil sample data, it is time-consuming and laborious to collect soil data; Secondly, the prediction accuracy of the model for long-term soil composition is reduced.

The main research contributions of this paper are summarized as follows:

Firstly, a method of improving BP neural network algorithm is proposed. As a prediction algorithm model, the convergence speed and prediction accuracy of the model can be improved;

Secondly, K-Mean algorithm is used as the implementation method of parcel grid optimization, which can realize the scientific division of parcels;

Thirdly, predict the soil nitrogen content by combining the local soil sampling data with the improved algorithm to improve the prediction accuracy of the algorithm model without increasing the cost of soil sampling, so as to realize the fertilization decision;

This paper is organized as follows. Section II introduces the related work of related algorithms. Section III introduces the establishment process of short-term prediction model as a long-term prediction model. Section IV introduces the classification method of land parcel gridding and divides the land parcel. In Section V, provides the prediction results and makes a comparative analysis. Section VI is the conclusion and plans the next step.

## 2 Related Work

J. W. Harrison et al [4] used random forest regression (RFR) to predict nitrogen (N) and phosphorus (P) concen-

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trations in forested streams in upstate New York, as Lu Lu [5] used a time series model to predict soil moisture and established prediction models for different soil layers with good results Shipeng Yu [6] used a linear model, BP neural network and fuzzy neural algorithm for groundwater salinity prediction, and obtained that the fuzzy neural algorithm was superior. In response to the shortcomings of BP networks which are prone to local optimum and slow convergence, Zhang Yu [7] fused chaos algorithm and genetic algorithm into BP neural network so as to realize an intelligent macro process planning method for STEP-NC 2.5D manufacturing features and verified its effectiveness and feasibility. Darren Li investigated a nitrogen nutrition diagnosis and prediction model for melon so as to apply fertilizer accurately [8]. Yanyan Cao, for the black land in Northeast China, which is the main grain producing area, studied the distribution law of black land fields and the fertilization strategy of black land, which has a positive effect on precise fertilization and black land protection [9].

## 3 Short-term Prediction Model of Soil Nitrogen Content

Artificial Neural Network (ANN) technology was born, which simulates certain mechanisms and mechanisms of the brain to achieve a certain aspect of function. Its advantage is that it has self-learning function, associative storage function and the ability to find optimal solutions at high speed, which is it can automatically establish the mapping relationship between input and output values and find the optimal solution [10]. Among the neural network models, BP neural network is one of the most widely used models. BP neural network is a multilayer feedforward neural network trained according to the error backpropagation algorithm proposed by David Runelhart [11]. The structure of this network consists of an input layer, an output layer, and several hidden layers, and the most basic three-layer structure is shown in Fig. 2. The input layer mainly realizes data input, reading and screening to prevent overfitting due to too many influencing factors; the hidden layer is the core of the network, which realizes the feature extraction of data, that is, calculating the output factor, and the number of hidden layers can be arbitrarily adjusted by the user. The output layer is obtained by computing the feature data extracted from the hidden layer using full connectivity according to the desired output form.

### 3.1 Principle Diagram of Artificial Intelligence Algorithm Model

BP neural network, as an important neural network model for artificial intelligence, is widely used because of its better nonlinear mapping ability, self-learning and self-adaptive ability, but its disadvantages are also more significant, such as the problems of local minima and slow convergence speed. In this paper, the BP neural network model is used as the base model, and the gray wolf algorithm is introduced to improve the convergence speed and accuracy of the BP neural network model prediction, and the backward learning mechanism is introduced to avoid the problem of falling into the local optimum. Therefore, the system flow chart of the entire AI algorithm model is shown in Fig. 1.

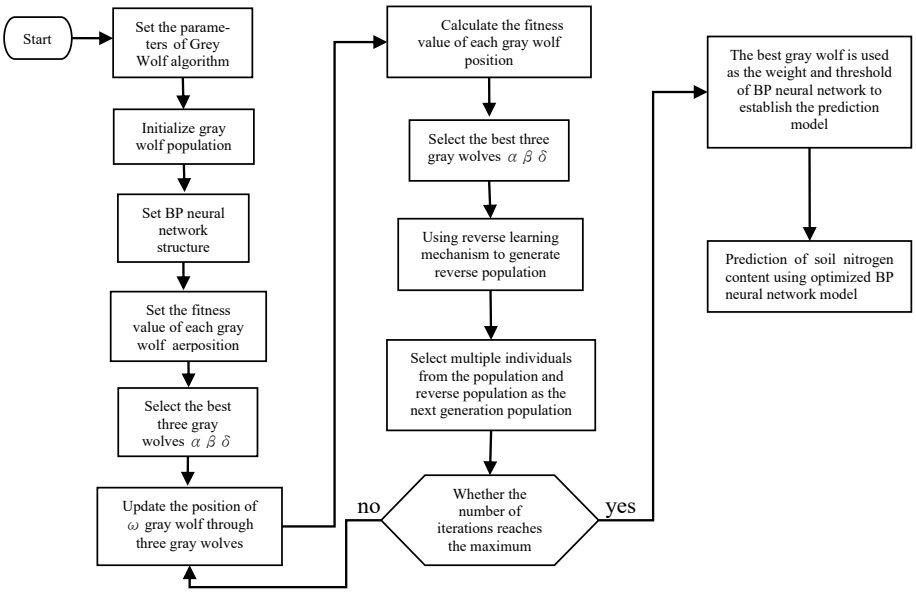


**Fig. 1.** Algorithm flow chart

### 3.2 Establishment of BP Neural Network Model

The structure of the network consists of an input layer, an output layer and several hidden layers. The input layer mainly realizes data input, reading and screening. The hidden layer is the core of the network and realizes the feature extraction of the data. The output layer is computed by using full connectivity on the feature data extracted from the hidden layer according to the desired output form. The basic model structure is as Fig. 2:

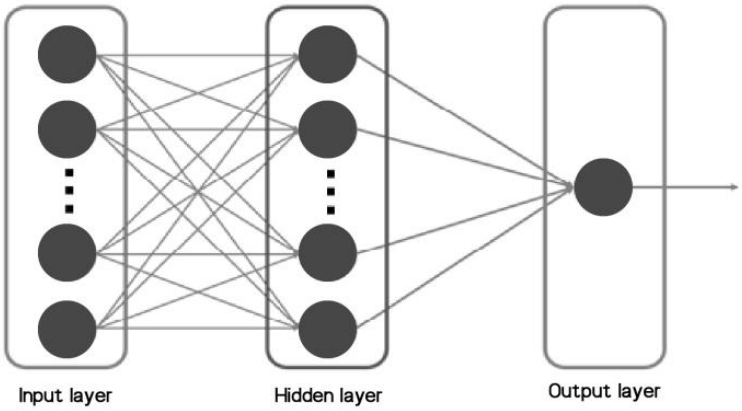


**Fig. 2.** Three layer BP network structure diagram

The forward transfer process of BP neural network is to calculate the output features by nonlinear transformation of the input information from the input layer through the hidden layer by layer, and forward transfer until the output of each computing unit; the reverse transfer process is to reverse the error of the output layer by layer from the output layer, in which the error of each unit in the hidden layer needs to be calculated continuously, and the error is used to correct the weights of the previous layer. The model establishment and training process are as follows.

(1) Set parameters such as the weight of each hidden layer, the number of nodes, the bias of neurons and the learning rate.

(2) Calculate the output of the hidden layer with the following formula.

$$H_k = f\left(\sum_{i=1}^{m} x_i * w_{ik} - a_k\right). \tag{1}$$

Where $H_k$ is the output of the $k$ th node of the hidden layer, $m$ is the number of input layer nodes, $w_{ik}$ is the connection weight from the $i$ th input layer node to the $k$ th hidden layer node, and the hidden layer node $k = 1, 2, \cdots, n$, $f(\ )$ is the activation function.

The Sigmoid function of smooth depression derivative is chosen as the activation function, thus mapping a real number to the (0,1) interval with the following function:

$$s(x) = \frac{1}{1+e^{-x}}. \tag{2}$$

(3) Obtain the output of the actual output, calculated as

$$O_k = \sum_{k=1}^{n}\left(H_k * w_{kj}\right) - b_j. \tag{3}$$

In the formula, $b_j$ is the bias, $j$ = 1, 2, ..., $s$.

(4) Establishment of back propagation process

Calculate the error value of the output layer with the following formula:

$$e_j = O'_j - O_j . \tag{4}$$

The error values are used to continuously correct the weight values of the previous layer, so the input layer to the implied layer weight value update is calculated as follows:

$$w_{ik} = w_{ik} + \theta H_k \left(1 - H_k\right) * x_i \sum_{j=1}^{s} \left(w_{kj} - e_j\right) . \tag{5}$$

In the formula, $\theta$ is the learning efficiency, and similarly, the formula for updating the weights from the implied layer to the output layer is as follows:

$$w_{ik} = w_{ik} + \theta H_k * e_j . \tag{6}$$

The threshold update process is obtained by the formula, and the threshold update formula for the input layer to the hidden layer is as follows:

$$a_k = a_k + \theta H_k \left(1 - H_k\right) \sum_{j=1}^{s} \left(w_{kj} * e_j\right) . \tag{7}$$

The implied layer to output layer threshold update formula is as follows:

$$b_j = b_j + e_j . \tag{8}$$

(5) Model termination training

Training is terminated when one of the following conditions is met.

a. The total error of the output is less than the set threshold.

b. The maximum value of all weight value changes is less than the set threshold.

c. The total number of training is equal to the set number.

### 3.3 Gray Wolf Algorithm to Improve the Convergence Speed and Prediction Accuracy of the Algorithm

Analyzing all the formulas in the reverse transfer process in 2.2, it can be concluded that the weight values and thresholds are important for the convergence speed and prediction accuracy of the model, so the optimal solution of the weight values and thresholds using the gray wolf algorithm to spherical, accelerate the convergence process and improve the prediction accuracy. The gray wolf algorithm classifies the population into four classes $\alpha$, $\beta$, $\delta$, $\omega$, from high to low according to the wolf [12]. The upper level hierarchy helps the lower level to search the optimal solution space region. The hierarchy diagram is as Fig. 3:

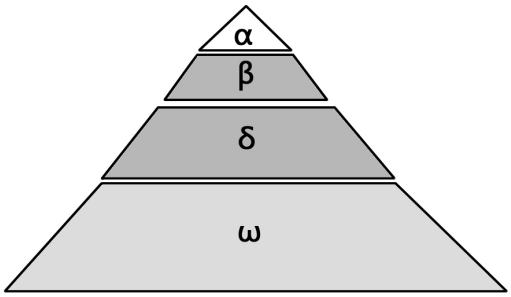


**Fig. 3.** Gray wolf hierarchy

Establishing a mathematical formula for the search process, firstly, according to the law of hunting, the wolves find the location of the prey and surround it, expressed by the formula:

$$D = \left| \vec{C} * \vec{X}_p(t) - \vec{X}(t) \right|. \tag{9}$$

In the formula, $D$ is the distance between the gray wolf and the prey, $\vec{C}$ is the coefficient vector, $\vec{X}_p$ is the position vector of the prey, $\vec{X}$ is the position vector of the gray wolf, and $t$ represents the number of iterations.

The formula for the location of the $t$+1th wolf is as follows.

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A} * D. \tag{10}$$

In the formula, $\vec{A}$ represents the coefficient vector, and the other parameters have the same meaning as formula 9.

For the coefficient vectors $\vec{A}$ and $\vec{C}$ are calculated as follows:

$$\vec{A} = 2\vec{a} * \vec{r}_1 - \vec{a}. \tag{11}$$

$$\vec{C} = 2\vec{r}_2. \tag{12}$$

In the formula, $\vec{a}$ is a convergence factor that decreases linearly from 2 to 0 as $t$ increases; $\vec{r}_1$ and $\vec{r}_2$ are random numbers that take values in the range of $[0,1]$.

Second, when the prey is surrounded, the wolves start hunting. The hunting process is led by $\alpha$, $\beta$ and $\delta$ guide the $\omega$ to surround the prey under the leadership $\alpha$. The formula for $\alpha$, $\beta$ and $\delta$ to track the prey position is as follows:

$$D_\alpha = \left| \vec{C}_1 * \vec{X}_\alpha - \vec{X} \right|. \tag{13}$$

$$D_\beta = \left| \vec{C}_2 * \vec{X}_\beta - \vec{X} \right|. \tag{14}$$

$$D_\delta = \left| \vec{C}_3 * \vec{X}_\delta - \vec{X} \right|. \tag{15}$$

Where $D_\alpha$, $D_\beta$ and $D_\delta$ represent the distances between the three wolves and other individuals, respectively, $\vec{X}_\alpha$, $\vec{X}_\beta$ and $\vec{X}_\delta$ represent the current positions of the three wolves, $\vec{C}_1$, $\vec{C}_2$ and $\vec{C}_3$ represent the random vectors, $\vec{X}$ represents the current position of the gray wolf.

The vector of omega individuals in the wolf pack advancing towards Alpha, beta and delta is denoted by $\vec{X}_1$, $\vec{X}_2$ and $\vec{X}_3$, then its formula is as follows.

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1 * \left( \vec{D}_\alpha \right). \tag{16}$$

$$\vec{X}_2 = \vec{X}_\beta - \vec{A}_2 * \left( \vec{D}_\beta \right). \tag{17}$$

$$\vec{X}_3 = \vec{X}_\delta - \vec{A}_3 * \left( \vec{D}_\delta \right). \tag{18}$$

Based on the results of $\vec{X}_1$, $\vec{X}_2$ and $\vec{X}_3$, the final position of the omega individual can be determined with the following formula.

$$\vec{X}(t+1)=\frac{\vec{X}_1+\vec{X}_2+\vec{X}_3}{3}. \tag{19}$$

Finally, when the prey is unable to move, the hunt is completed by attacking the prey.

In the gray wolf algorithm, $\vec{A}$ is linearly decreasing and prone to local optimum. For this reason, a random value $C$ is introduced in the algorithm, which can avoid the emergence of local optimum.

### 3.4 Inverse Learning to Avoid Local Optimal Solutions

The core idea of inverse learning is to improve the search efficiency while evaluating the inverse solutions of the candidate solutions in the solution space, which is expressed in the mathematical formula as:

$$X_i'=a+b-X_i, X_i\in[a,b]. \tag{20}$$

In the formula, $X_i$ is the candidate solution, $X_i'$ is the directional solution, $a$ is the lower bound of the solution space, and $b$ is the upper bound of the solution space.

After improvement, the weight value and threshold value in the BP neural network model are regarded as individuals in the gray wolf algorithm, and the optimal solution of the weight value and threshold value can be found by the gray wolf algorithm, which can improve the convergence speed and prediction accuracy, and at the same time, in order to avoid the appearance of the local optimal solution, the current value and the reverse value are compared in the calculation of the reverse learning mechanism, while random numbers are introduced to, achieve the circumvention of the local optimal solution.

## 4. Combination of Local Sampling and Improved Neural Network to Improve Forward Prediction Accuracy

The improved BP neural network algorithm in the previous section requires existing nitrogen data from previous years to predict the soil nitrogen content in the next 1-2 years, which will be biased if the forward nitrogen content is predicted due to the accumulation of errors from year to year. This chapter uses local sample sampling to assist the prediction algorithm to eliminate the error accumulation and ensure the accuracy of the forward prediction without increasing the labor time cost.

First, local sampling points are selected from the whole plot and the soil nitrogen content is measured manually; second, the soil nitrogen content is predicted using the model in the previous section and the difference between the predicted and measured values is calculated; again, the unsampled points are predicted and the combined prediction difference is obtained by weighting, and finally, the weight sum of the predicted and combined differences is calculated to obtain the reddest soil nutrient content.

### 4.1 K-Means Algorithm to Optimize the Selection of Local Sampling Points

Sampling all the soils in the target plot will increase a lot of manual testing costs, while a reasonable selection of local sample soils can get the real ideal values of soil nitrogen content with reducing the testing costs.

K-Means algorithm is a data mining algorithm based on division and unsupervised [13]. The algorithm judges the data attributes based on their similarity and divides those with high similarity into the same class, and this paper uses Euclidean distance to judge the similarity [14].

(1) According to the K-Means idea, the central region of each class is determined first. There is no prior data before the first classification, so a random method is used to select the central point for clustering.

(2) The target parcel is clustered, and the target parcel is a 1500 m2 parcel centered at longitude: 118.93555 and latitude: 39.41455. Based on the randomly selected centers, the clustering is performed by the algorithm, and the clustering ends when the specified number is satisfied or when the class division according to the cluster-

ing centers calculated in the previous round is the same as the classes divided in the previous round or when the specified number is satisfied or when the clustering centers calculated according to the newly divided classes are the same as the clustering centers in the previous round or when they are less than the set minimum error sum of squares.

(3) Determine the optimal number of classifications

First set a smaller classification number k. When the classification number is small, that is, when the classification number is smaller than the true value, the distortion degree will be reduced to a great extent for each increase of 1 in the classification number k; when the classification number k is larger than the true value, the distortion degree changes less obviously for each increase of 1. The values of k and the degree of aberration are drawn into a graph to find the turning point, and the relationship between the number of classifications and the degree of aberration of the predicted data is obtained according to the soil nutrient clustering algorithm as shown in Fig. 4, from which it can be seen that the optimal number of classifications is 6, which is k is 6.

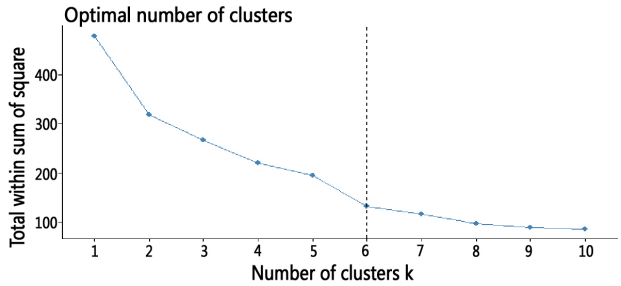


**Fig. 4.** Forecast classification number and distortion degree

The k as 6 is input into the K-Means algorithm structure to get the clustering results, as shown in Fig. 5, the land is divided according to the clustering results as shown in Fig. 6, and the sampling points are optimized to get 12 and marked with letters A-M respectively, and the 12 land sampling points meet the low-cost manual detection expectation and can be manually sampled and detected.

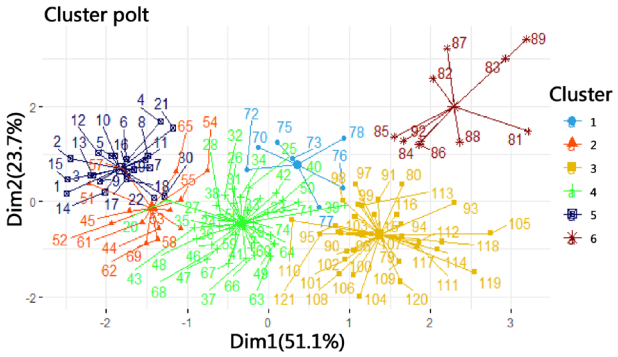


**Fig. 5.** Clustering results of diction data

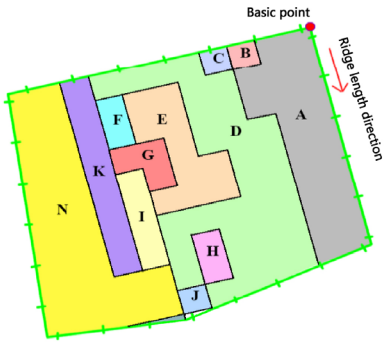


**Fig. 6.** Forecast sampling layout

### 4.2 Difference Calculation

Assuming that the assay data of soil nutrients are $z$ and the predicted data of soil nutrients are $z^{'}$, the difference of soil nutrients $\Delta z$ is calculated as follows.

$$\Delta z = z - z' . \tag{21}$$

Using the distance inverse ratio method, the distance inverse ratio formula is introduced based on the difference calculation formula, and the nitrogen content of the soil around the sampling point is predicted by the formula.

$$z_0 = \frac{\sum_{i=1}^{n} \frac{1}{(D_i)^p} \Delta z_i}{\sum_{i=1}^{n} \frac{1}{(D_i)^p}} + z_0' . \tag{22}$$

In the formula, $z_0$ is the value of the precomputed point; $z_i$ is the value of the $i$ th known point; $n$ is the number of known points; $D_i$ is the distance from the precomputed point to the $i$ th known point, $D_i = \sqrt{(x_0 - x_i)^2 - (y_0 - y_i)^2}$ , $(x_0, y_0)$ is the coordinate of the predicted point, $(x_i, y_i)$ is the coordinate of the $i$th known point; $p$ is the power of the distance.

$z_0'$ is the predicted soil nutrient value at the pre-calculated point; $\Delta z_i$ is the soil nutrient difference at the $i$ th known point.

## 5. Analysis of Predicted Results

### 5.1 Prediction Results of Soil Nitrogen Content

Using the improved BP network model in Chapter 2, the nitrogen values of the optimized sampling points were predicted, and the prediction mathematical model was input into MATLAB for simulation runs. The comparison graph of the prediction results is shown in Fig. 7, the predicted value of nitrogen using the improved BP neural network, that is, the brown curve, is closer to the blue curve of the true value of soil nitrogen. Difference between the measured and predicted values of the sampling points was counted and used as the data base for subsequent predictions, as shown in Table 1.

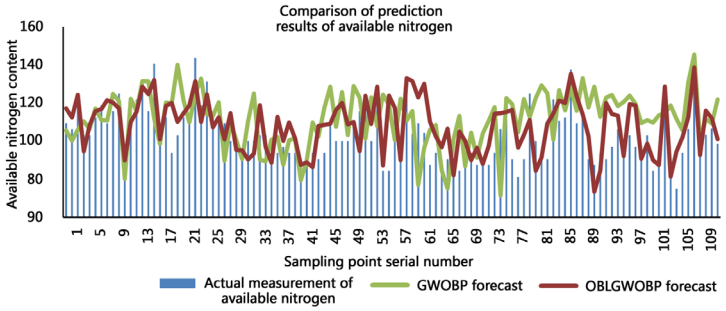


**Fig. 7.** Comparison of nitrogen prediction results

**Table 1.** Prediction and measured values of soil nitrogen content

| Sampling point | Measured value | Forecast value |
|---|---|---|
| A | 103.00 | 108.30 |
| B | 103.00 | 110.03 |
| C | 99.88 | 95.23 |
| D | 103.00 | 96.78 |
| E | 99.88 | 109.02 |
| F | 99.88 | 89.97 |
| G | 87.40 | 100.07 |
| H | 87.40 | 110.15 |
| I | 87.40 | 88.03 |
| J | 90.52 | 116.32 |
| K | 110.52 | 121.25 |

In formula 22 by bringing in the numerical comparison, after the optimization of the soil sampling points, choose the difference weight method between the actual measured value of the sampling points and the predicted value, and finally in the difference, the final selection of the number of sampling points is 8 and the power of the distance is 1. The comparison results between the predicted value obtained by using different prediction points and the improved BP algorithm and the actual value of nitrogen are as shown in Fig. 8:

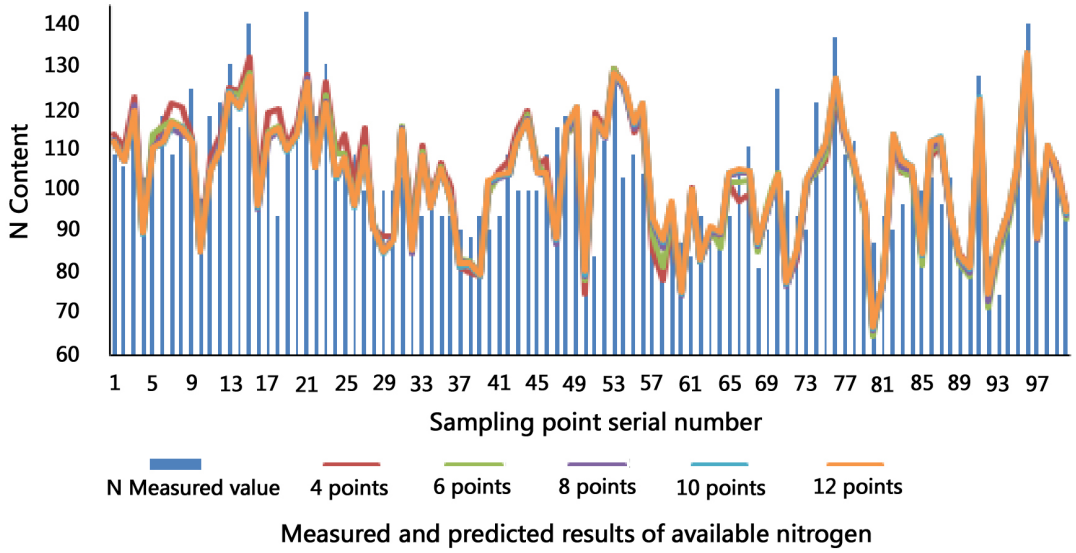


**Fig. 8.** Measured curve of nitrogen prediction

### 5.2 Comparison of Accuracy of Soil Nitrogen Content Prediction

Calculate the prediction accuracy $\alpha$ of soil nutrient content based on the results of soil nutrient content prediction.

$$\alpha = 1 - \frac{|z' - z|}{z}. \tag{23}$$

**Table 2.** Prediction accuracy of soil nitrogen content

| Soil nutrient | Division method | Power | Points used for prediction | | | | |
|---|---|---|---|---|---|---|---|
| | | | Four points | Six points | Eight points | Ten points | twelve points |
| Measured value | Mesh optimization | p=1 | 90.01 | 89.79 | 89.48 | 89.52 | 89.44 |
| | | P=2 | 90.10 | 90.03 | 89.86 | 89.88 | 89.83 |
| | | P=3 | 90.10 | 90.08 | 90.02 | 90.02 | 90.01 |
| Difference value | Mesh optimization | p=1 | 90.99 | 91.16 | **91.19** | 91.14 | 91.18 |
| | | P=2 | 90.47 | 90.76 | 90.92 | 90.91 | 90.94 |
| | | P=3 | 89.87 | 90.08 | 90.20 | 90.22 | 90.24 |

It can be seen from the Table 2 analysis that when the soil nutrients are obtained by the difference method, and the plots are clustered by the grid optimization method, the prediction model is used. At the same time, the power of the prediction model is 1, which can reach the highest the prediction accuracy.

## 6. Conclusion

The improved algorithm model described in this paper realized the expectation of rapid convergence and improved prediction accuracy, and solved the problem that the accuracy of the prediction results of the previous algorithm models for long-term soil nitrogen content was reduced. In order to reduce the cost of soil element sampling, the improved algorithm is used to optimize the soil grid. The optimized grid is the soil sampling point. On the premise of not affecting the overall sampling data sample results, the number of sampling points is greatly reduced, so as to achieve the accurate prediction of the overall nitrogen content of the plot and the accurate fertilization decision. Although nitrogen plays an important role in the growth cycle of muskmelon, other elements such as phosphorus and potassium are also very important. In the future, this paper will continue to make accurate prediction research on all elements that affect the growth cycle of muskmelon.

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