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A neural network ensemble method for precision fertilization modeling

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ABSTRACT

There exists a nonlinear relationship between fertilizer input and soil nutrient level. To calculate the fertilization rate more precisely, a novel neural network ensemble method has been proposed, in which the K-means clustering method is used to select optimal networks individually and a Lagrange multiplier is used to combine these selected networks. On the basis of the above neural network ensemble method, a fertilization model is constructed. In this model, the soil nutrient level and the fertilization rate are taken as neural network inputs and the yield is taken as the output. This model transforms the calculation of the fertilization rate into solving a programming problem, and can be used to calculate the fertilization rate with maximum yield and maximum profit as well as to forecast the yield. Furthermore, this fertilization model has been tested on fertilizer effect data. The results show that the value forecast using the neural network ensemble is more accurate than that obtained with individual neural networks. The fertilization model constructed in this paper not only can precisely simulate the nonlinear relationship between yield and soil nutrient level, but also can adequately make use of the existing fertilizer effect data.

1. Introduction

Precision fertilization is a key component of precision agriculture; the basic idea is to divide the field into grids using GPS, then test for soil nutrients and compute the fertilizer input needed using the fertilization model, and finally fertilize using a variable rate applicator. Practical experience shows that precision fertilization can decrease fertilizer use, increase crop yield, balance soil nutrients [1] and abate environmental pollution.

There are more than sixty fertilization models extant in crop fertilization research and practice. However, the existing models contradict actual production; a lot of data cannot be used to guide the production practice [2]. In traditional fertilization methods, the nutrient balance method is widely used, but this formula needs a lot of parameters such as soil nutrient level, target yield, adjustment coefficient, nutrient application rate, and so on, and cannot reflect the interaction of different nutrients.

In recent years, China has invested a lot of funds in soil testing and formulated fertilization. Also, a lot of "3414" experiments are conducted on various districts. Such an experiment is mainly used for the simulation of a ternary quadratic equation, followed by computation of the optimal fertilizer input. But practice has proved that this simulation often fails, and many results are discarded, which represents a huge waste of human, material and financial resources [3].

To solve the above problems, some soft computing methods have been used. As regards the nonlinear relationship between fertilizer application rate and its influencing factors (soil nutrients, yield, etc.), some different forms of neural networks have been used in fertilization recommendation [4–6] and yield prediction procedures [7]. In addition, a neural network ensemble method was used in land evaluation [8] and a genetic algorithm was used in fertilization model fitting [9].

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Table 1
Nutrient concentration of each field.

Field No.	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
N (mg/kg)	102	112	102	138	122	125	112	116	106	120
P (mg/kg)	45	38	51	42	39	41	66	60	51	45
K (mg/kg)	156	162	160	145	149	157	157	153	149	153

Table 2
“3414” experiment scheme.

Treatment No. (#)	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12	T13	T14
N fertilizer input (kg/mu)	0	0	6	12	12	12	12	12	12	12	18	6	6	12
P fertilizer input (kg/mu)	0	5	5	0	2.5	5	7.5	5	5	5	5	2.5	5	2.5
K fertilizer input (kg/mu)	0	5	5	5	5	5	5	0	2.5	7.5	5	5	2.5	2.5

Table 3
The yield obtained from a “3414” experiment conducted on each field (kg/mu).

	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
T1	479	480	509	613	540	550	623	609	529	554
T2	537	539	570	687	606	617	699	683	593	621
T3	578	580	614	740	652	665	752	736	639	668
T4	592	594	629	758	668	681	770	754	654	685
T5	643	645	683	823	725	739	836	818	710	743
T6	669	671	710	856	755	769	870	851	739	773
T7	662	664	703	847	747	761	861	842	731	765
T8	602	604	640	771	680	693	784	767	665	697
T9	612	614	650	783	690	703	796	778	676	707
T10	620	622	659	794	700	713	807	789	685	717
T11	612	614	651	784	691	704	797	779	676	708
T12	542	544	576	694	612	623	705	690	599	627
T13	565	566	600	723	637	649	735	719	624	653
T14	597	599	635	765	674	687	777	760	660	691

In conventional fertilization models based on neural networks, soil nutrients and target yields are taken as inputs and the fertilizer application rate is taken as the output, which will cause the following two problems. Firstly, before computing the fertilization rate, a maximum target yield should be provided; however, it is often difficult to forecast the target yield, so this will inevitably cause a larger error in the fertilization rate. Secondly, all these methods adopted a single neural network to simulate, but in view of the instability of a single network, its forecasting accuracy is not high and its generalization capacity is not great.

In order to address the above mentioned problems, in this study, the following measures are taken. To solve the first problem, the soil nutrient concentration and fertilization rate are taken as neural network inputs and yield is taken as the neural network output. The computation of the fertilization rate is transformed into solving a programming problem. To solve the second problem, a novel neural network ensemble method based on K-means clustering and a Lagrange multiplier is proposed.

2. Materials and methods

2.1. Data description

The experimental site is located in a maize field in YuShu city in China, which is a typical zone of black soil. All fields have consistent conditions such as soil type, crop variety and climate, and so on. In this study, we assume that there are only six factors influencing crop yield, which are soil nitrogen (N), phosphorus (P) and potassium (K) concentration and N, P and K fertilizer input.

The experimental data are obtained from 10 fields at the experimental site and a “3414” experiment is conducted on every field. In a “3414” experiment, 3, 4, 14 respectively denote the 3 properties (N, P and K levels), 4 fertilization rate levels and 14 treatments. In the four fertilization rate levels, level 0 refers to no fertilizer input, level 2 is the approximation value of the local optimum fertilization rate, level 1 $=$ level 2 $\times$ 0.5, level 3 $=$ level 2 $\times$ 1.5 (this level refers to excess fertilizer input).

In 2007, “3414” datasets from 10 experimental fields were obtained by sampling, fertilizing and yield surveying. The nutrient concentration in each experimental field is given by Table 1. The “3414” experiment scheme is given in Table 2. The yield of each treatment in each field is given by Table 3.

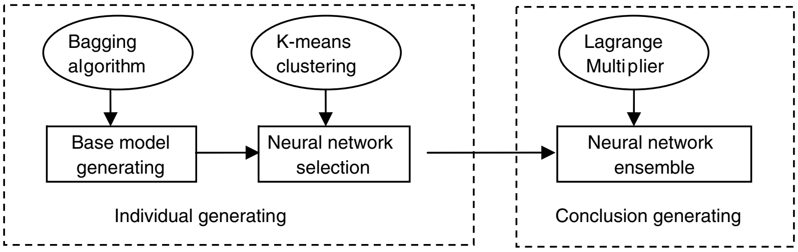

Fig. 1. Neural network ensemble method in this paper.

2.2. The basic laws in crop fertilization

There are many laws in crop fertilization, but the following four are representative:

(i) *Fertilization law* 1: the theory of nutrient return, which refers to fertilizer being needed to compensate for the nutrient absorbed by crop growth.
(ii) *Fertilization law* 2: the law of minimum nutrient, which refers to crop yield being restricted by the minimum nutrient present.
(iii) *Fertilization law* 3: the law of diminishing returns, which refers to the fact that when the fertilization rate reaches a certain degree, the increase in crop yield will stop or slow down.
(iv) *Fertilization law* 4: the law of integrated effects of factors, which refers to crop yield being determined by multiple nutrients such as N, P and K.

The importance of the above laws lies in them often being taken as an evaluating standard for a fertilization model. A reasonable fertilization model should conform to the four laws.

Obviously, the fertilization model proposed in this paper conforms to *Fertilization laws* 1 and 4. In the following, we will find that this model also conforms to *Fertilization laws* 2 and 3.

2.3. The neural network ensemble method based on K-means clustering and a Lagrange multiplier

The neural network ensemble was proposed by Hansen and Salamon [10] in 1990; the aim is to improve the generalization capability of the neural network system by training multiple neural networks and combining them.

The ensemble method is composed of individual generatings and conclusion generating. Also, the individual generating steps include base model generating and neural network selection. In this paper, the algorithm adopted in each step is given in Fig. 1.

In the individual generating stages, the Bagging algorithm is adopted to generate the base model and the K-means clustering algorithm is used to select the optimal individuals. In the conclusion generating stage, the Lagrange multiplier method is used to combine the selected individuals. Finally, a fertilization model based on the neural network ensemble method is built.

2.3.1. Neural network individual generatings

(1) *Generating the base model using the Bagging algorithm*

In this paper, the Bagging algorithm is adopted to train BP neural networks to ensure diversity of the generated neural network set, and at the same time, in order to ensure the effectiveness of the individual neural network, only the neural networks whose forecasting error is less than the predefined threshold are selected.

The basic idea of the Bagging algorithm is sampling repeatedly, where the training set for various neural networks is composed of some cases randomly selected from the original dataset and the training cases can be selected repeatedly. This method increases the diversity of neural networks and furthermore improves the generalization capability.

Before training, the training set, validation set and testing set have been standardized within [0, 1].

(2) *Selecting the neural network using K-means clustering*

For the neural network selection, in 2002, Zhou Zhi-Hua [11] proposed the theory that "many could be better than all", in which it is proposed that selecting neural network individuals with high precision and strong diversity will be better than using all neural networks. Li Kai et al. [12] proposed a selective approach to neural network ensemble studies based on clustering techniques.

In this paper, the K-means clustering technique is used to select the optimal network. In order to measure neural network similarity, a formula is introduced. Assume that f_i and f_j are two neural networks for a dataset and the forecasting results corresponding to the i-th output are y_{ik} and y_{jk} respectively. Then the similarity between the two neural networks can be defined as

$$S(f_i, f_j) = -\sqrt{\frac{1}{k}\sum_{k=1}^{m}(y_{ik} - y_{jk})^2}.$$

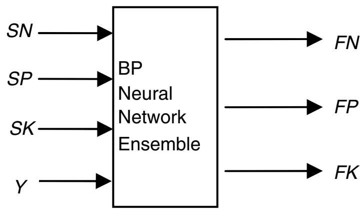

Fig. 2(a). The 4-x-3 model.

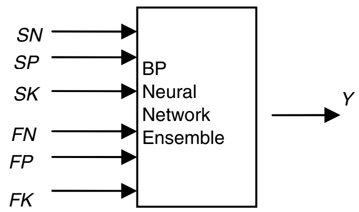

Fig. 2(b). The 6-x-1 model.

On the basis of above formula the neural network individuals can be clustered through the K-means algorithm. For each cluster, an individual network is randomly selected; taken together, they constitute a new neural network set to be combined.

2.3.2. Conclusion generating by the Lagrange multiplier method

The main idea of the Lagrange multiplier method is that it takes the square sum as the object function and the weight coefficient is determined by minimizing the object function.

Suppose that a neural network ensemble is composed of n neural networks $f_1, f_2, \ldots, f_n$, and each of them has m outputs.

Assume that the actual value at j is y_j $(j = 1, 2, \ldots, m)$ and the forecasting value of the i-th method at j $(j = 1, 2, \ldots, m)$ is f_{ij}; then the forecasting error can be described as

$$e_{ij} = y_j - f_{ij}.$$

Assume that K_i $(i = 1, 2, \ldots, n)$ is the weight of the i-th neural network, with $K_i \geq 0$ and $\sum_{i=1}^{n} K_i = 1$; then the combined forecasting error at j $(j = 1, 2, \ldots, m)$ is

$$e_j = y_j - f_j = \sum_{i=1}^{n} K_i e_{ij} = [K_1, K_2, \ldots, K_n] \bullet [e_{1t}, e_{2t}, \ldots, e_{nt}]^T$$
$$= \left[e_{1j}, e_{2j}, \ldots, e_{nj}\right] [K_1, K_2, \ldots, K_n]^T .$$

Let $K = [K_1, K_2, \ldots, K_n]^T$, and $E_i = [e_{i1}, e_{i2}, \ldots, e_{im}]^T$ (E_i is the forecasting error vector for number i); then the forecasting error matrix of the assemble model is $e = [E_1, E_2, \ldots, E_n]$ and its square sum is $E = e^T e$.

Let J represent the error sum of squares for the weighted forecasting method; then $J = \sum_{j=1}^{m} e_j^2$, defining R as the vector whose components are all 1s, namely $R = [1, 1, \ldots, 1]^T$. Then the constraint condition can be adapted as $R = R^T K = 1$.

Now, under the above constraint, the weighted coefficient vector K which will minimize J will be obtained. The related theorems are given as follows:

Theorem 1. *To satisfy the constraint, the optimal weighted coefficient vector that makes $J = K^T EK$ minimized is $K = (E^{-1}R)/(R^T E^{-1}R)$, in which E^{-1} is the matrix inverse of E.*

Theorem 2. *Given $J_{\min} = \min\{K^T EK\}$, then $J_{\min} = \{1/(R^T E^{-1}R)\}$.*

This method ensures that the weighted coefficient of the model that is of larger error sum of squares is less, which makes the error sum of squares of the combined model as low as possible.

According to the above formula, the neural network ensemble method based on the Lagrange multiplier is described as

$$y_{ensemble,j} = \sum_{i=1}^{n} K_i f_{i,j}$$

where $y_{ensemble,j}$ is the j-th output of the combined neural network and $f_{i,j}$ is the k-th output of the i-th neural network individually.

2.4. The precision fertilization model based on the neural network

There are two forms of neural network-based fertilization models. One is the 4-x-3 model, whose inputs are the nutrient contents of N, P and K and the crop yield and whose outputs are fertilization rates for N, P and K. The other is the 6-x-1 model, whose inputs are the nutrient contents of N, P and K and the fertilization rates for N, P and K and whose output is the yield. The details can be seen in Figs. 2(a) and 2(b). In this figure, Y denotes the yield, SN, SP, SK denote the nutrient concentrations of N, P, K in the soil, FN, FP, FK denote the N, P and K fertilization rates.

The x in 4-x-1 and 6-x-1 denotes the neuron number of the hidden layer, which can be obtained according to the following formula: $n_1 = \sqrt{n+m} + a$, where n_1, n and m are respectively the neuron numbers of the hidden layer, input layer and output layer and a is a constant between 1 and 10. Obviously, the determination of the neuron number needs to be validated repeatedly.

The 4-x-3 model needs estimation of the target yield before computing the fertilization rate, but generally it is difficult to estimate the target yield accurately, which will cause inaccuracy of the fertilizer input. So, in this paper, the 6-x-1 model is adopted, which can be described as a function:

$$Y = ANN(SN, SP, SK, FN, FP, FK), \quad \text{where } ANN \text{ is the function name.}$$

On the basis of the 6-x-1 model, calculating the fertilization rate with maximum yield and maximum profit requires solving the following programming problem (1) and (2):

$$\begin{cases} \max Y = ANN(SN, SP, SK, FN, FP, FK) \\ \text{s.t.} \quad 0 \le FN \le fn_{\max},\ 0 \le FP \le fp_{\max},\ 0 \le FK \le fk_{\max},\ SN = sn,\ SP = sp,\ SK = sk \end{cases} \tag{1}$$

where $fn_{\max}, fp_{\max}, fk_{\max}$ respectively denote maximum application rates of N, P and K fertilizer and sn, sp, sk respectively denote N, P and K concentrations in an actual field;

$$\begin{cases} \max P = Y \times p_y - (FN \times p_n + FP \times p_p + FK \times p_k) \\ \text{s.t.} \quad 0 \le FN \le fn_{\max},\ 0 \le FP \le fp_{\max},\ 0 \le FK \le fk_{\max},\ SN = sn,\ SP = sp,\ SK = sk \end{cases} \tag{2}$$

where p_y denotes the market price of maize, p_n, p_p, p_k respectively denote market prices of N, P and K fertilizer.

3. Results and analysis

3.1. Determination of the neural network parameters

The BP neural network is adopted and all algorithms are implemented with MATLAB 7. By testing, we find that the neuron number of the hidden layer is 7, so the network is of 6–7–1 structure. In addition, the linear function *purelin* and the S-tangent function *tansig* are respectively adopted as the neuron transmitting functions of the output layer and the hidden layer. The BP algorithm with 'Momentum' is adopted as the learning rule.

The data from fields 1–8 are taken as the training set (112 samples). The data from field 9 are taken as the validation set (14 samples). The data from field 10 are taken as the testing set (14 samples). In this experiment, 500 sub-nets are generated, which are classified with 50 classes using the K-means clustering algorithm, namely generating 50 representative networks to be combined.

3.2. Comparison of forecasting results

To test the effectiveness of the Lagrange multiplier method, it is compared with optimum sub-network (OSN). The so-called OSN is obtained from the originally generated neural network set, which is of minimum prediction error.

For the field 10, the RMSE (root mean square error) of the Lagrange multiplier method and the optimal sub-network are respectively 0.98 and 1.80. The relative error between the forecast yield and actual yield is given in Fig. 3. The results show that the relative error of the Lagrange multiplier method is remarkably less than that of the OSN, which proves that the forecasting accuracy of the neural network ensemble method based on the Lagrange multiplier is higher than those of any of the neural networks individually in the neural network set initially generated.

3.3. Calculating the fertilization rate using the fertilization model based on the neural network ensemble method

For field 10,

① $SN = 120$ ppm, $SP = 45$ ppm, $SK = 153$ ppm,
② $0 \le FN \le 18$ kg, $0 \le FP \le 7.5$ kg, $0 \le FK \le 7.5$ kg,
③ $Y = ANN(120, 45, 153, FN, FP, FK)$,
④ $p_{\mathrm{n}} = 3.91$ yuan, $p_{\mathrm{p}} = 4.85$ yuan, $p_{\mathrm{k}} = 4.8$ yuan, $p_{\mathrm{y}} = 1.4$ yuan.

Fig. 4 depicts the relationship between yield and FN at different levels of FP and FK. Fig. 5 is a contour map of yield, which depicts the relationship between yield and FP and FK when FN is at level 2.

From Fig. 4, we can work out that, under the condition of keeping P and K fixed, the crop yield initially shows a linear increase trend with increase of FN, but with further increase of FN, the yield begins to slow down, which conforms to the law of diminishing returns (*Fertilization law* 3). On the other hand, the crop maximum yield begins to rise with increase of FP and FK (increasing from 0 to 3, then to 6 respectively), which shows that under the condition of P and K deficiency, no matter how great FN is, the yield will not increase, which conforms to the law of minimum nutrient (*Fertilization law* 2).

Similarly, from Fig. 5, we can find that when FN is at level 2, the crop yield initially rises with increase of FP and FK. When FP and FK have nearly reached level 2, the yield maximizes.

Fertilizer input with maximum yield and maximum profit is given by Table 4.

From Table 4, we can see that the fertilizer input with maximum profit is a little lower than that with maximum yield, so if the fertilizer price is considered, the maximum yield may not bring the maximum profit.

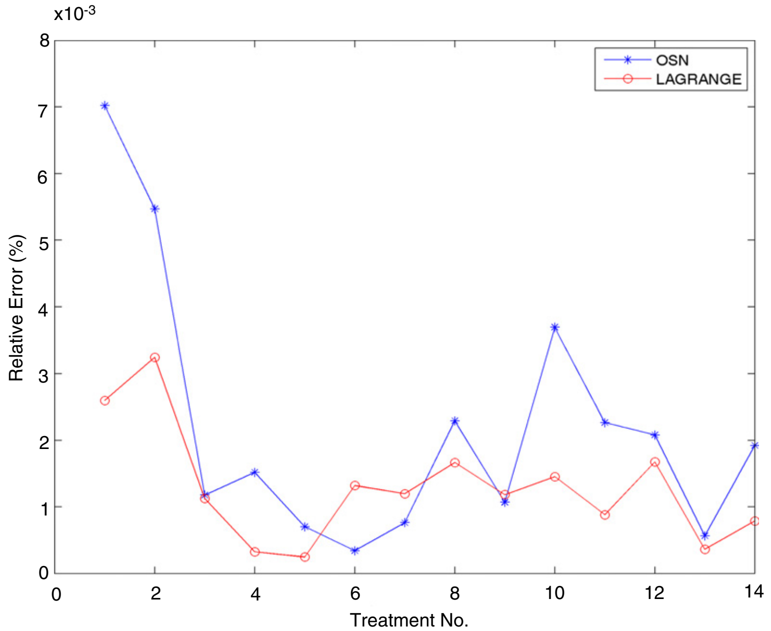

Fig. 3. Relative error of yield forecasting.

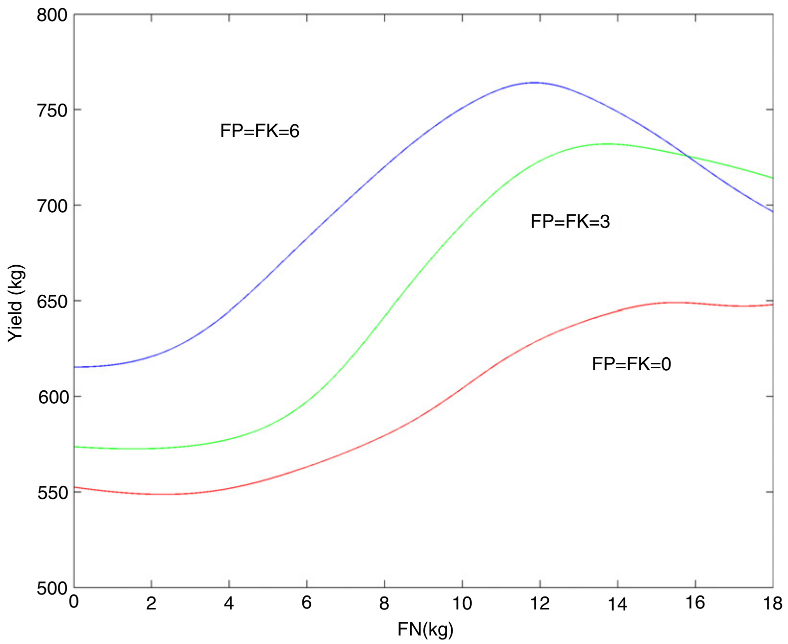

Fig. 4. Relationship between yield and *FN* at different fertilization levels, *FP* and *FK*.

Table 4
Fertilizer input in different fertilizing schemes.

Fertilizing scheme	*FN* (kg/mu)	*FP* (kg/mu)	*FK* (kg/mu)	Yield (kg/mu)	Profit (R.M.B.)
Fertilizer input with maximum yield	12.20	5.16	5.02	772.42	984.55
Fertilizer input with maximum profit	12.26	4.38	4.66	770.49	987.18

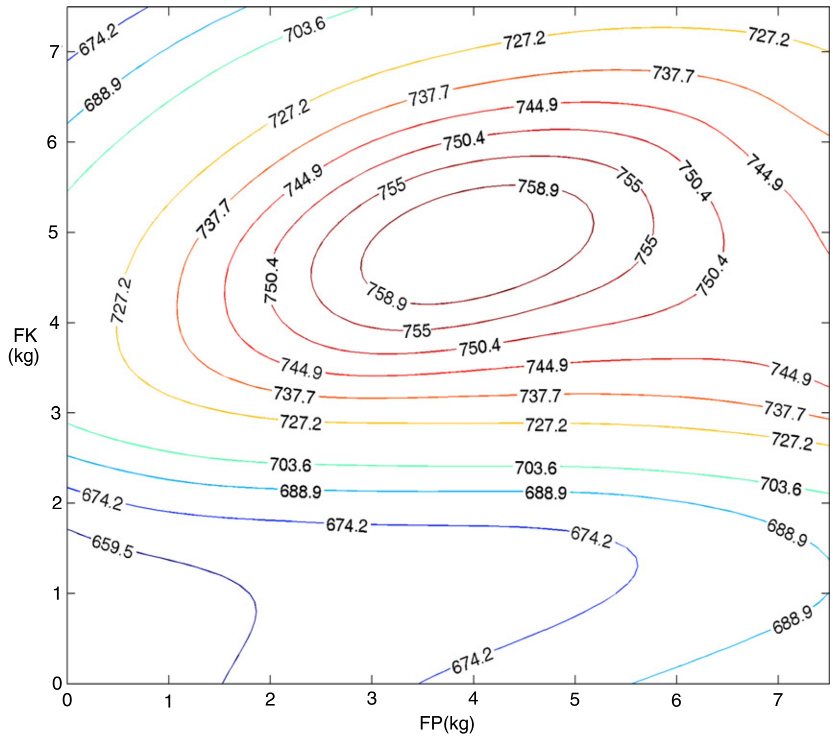

Fig. 5. Relationship between yield and *FP*, *FK* when *FN* is at level 2.

4. Conclusion

A neural network ensemble method based on K-means clustering and a Lagrange multiplier has been proposed and applied in crop precision fertilization.

The 6-x-1 mode adopted in this paper not only accords with causality but also can predict yield. On the basis of this neural network model, the computing of the fertilizer application rate is transformed into solving two programming problems, which can obtain the fertilization rate with maximum yield and maximum profit.

This model can make full use of "3414" data. Also, as a quantitative model, it can be used to guide precision fertilization.

Of course, in some cases, the fertilizer application rate obtained from this model should be revised according to the actual production and domain expert experience.

There is a basic assumption in this model: water, temperature and crop varieties of different fields are basically uniform. In order for this model to be more widely and generally adopted, some other factors influencing yield such as organic matter, *PH*, and moisture content should be considered. At the same time, more sample data should be included so that the forecasting value becomes more accurate. This will be our future work.

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References

[1] Shuhui Zhang, Chenglin Ma, et al., Experimental study on the influence of variable rate fertilization on maize yield and soil nutrients, Transactions of the CSAE 22 (8) (2006) 64–67.
[2] Yan-lin Hou, Shou-lun Chen, Summarization of fertilization model research, Chinese Journal of Soil Science 35 (4) (2004) 493–501.
[3] Sheng-Rui Wang, Xin-Ping Chen, Xiang-Zhao Gao, et al., Study on simulation of "3414" fertilizer experiments, Plant Nutrition and Fertilizer Science 8 (4) (2002) 409–413.
[4] Dragoljub Pokrajac, Zoran Obradovic, A neural network-based method for site-specific fertilization recommendation. California USA: ASAE Annual International Meeting, Sacramento, 2001.
[5] D. Pokrajac, Z. Obradovic, Neural network-based software for fertilizer optimization in precision farming, Neural Networks 3 (2001) 2110–2115.

[6] Cheng Lin Ma, Caicong Wu, Shuhui Zhang, et al., Decision making method for variable-rate fertilization based on data envelopment analysis and artificial neural network, Transactions of the CSAE 20 (2) (2004) 152–155.
[7] Georg Ruß, Rudolf Kruse, Martin Schneider, et al. Data mining with neural networks for wheat yield prediction, in: 8th Industrial Conference on Data Mining, ICDM, 2008, pp. 47–56.
[8] Yueju Xue, Yueming Hu, Jingfeng Yang, et al., Land evaluation based on SFAM neural network ensemble, Transactions of the CSAE 24 (3) (2008) 184–188.
[9] Miao Li, Zhang Jian, Ze-lin Hu, An algorithm of fertilization model fitting based on mixed intelligent computation, in: Advanced Computer Control, ICACC, 2009.
[10] L.K. Hansen, P. Salamon, Neural network ensembles, IEEE Transactions on Pattern Analysis & Machine Intelligence 12 (10) (1990) 993–1001.
[11] Zhou Zhi-Hua, Wu Jianxin, Tang Wei, Ensembling neural networks: Many could be better than all, Artificial Intelligence 137 (1–2) (2002) 239–263.
[12] Kai Li, Houkuan Huang, A selective approach to neural network ensemble based on clustering technology, Journal of Computer Research and Development 42 (4) (2005) 594–598.