Identification model of multi-layered neural network parameters and its applications in the petroleum production

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Abstract: This paper creates a LM (Levenberg-Marquardt) algorithm model which is appropriate to solve the problem about weights value of feedforward neural network. On the base of this model, we provide two applications in the oilfield production. Firstly, we simulated the functional relationships between the petrophysical and electrical properties of the rock by neural networks model, and studied oil saturation. Under the precision of data is confirmed, this method can reduce the number of experiments. Secondly, we simulated the relationships between investment and income by the neural networks model, and studied invest saturation point and income growth rate. It is very significant to guide the investment decision. The research result shows that the model is suitable for the modeling and identification of nonlinear systems due to the great fit characteristic of neural network and very fast convergence speed of LM algorithm.

Key words: neural networks model; relationships between the petrophysical and electrical properties of the rock; investment income; Levenberg-Marquardt learning algorithm

1 Introduction

Neural network has been successfully used in control engineering. The nonlinear functional mapping properties of neural networks are central to their use in control. The well approaching capabilities of neural networks for nonlinear function and the improvement of the identification methods of neural networks parameters has made them become important techniques and methods in the realm of modeling, identification and control of nonlinear systems[1-6].

To train the weights of the multi-layered feedforward neural network, the back propagation algorithm (BP algorithm) based on gradient descent direction of search was mainly used[6,7]. The drawback of BP algorithm converges slowly and is difficult to reach the satisfied precision[8,9]. Recently, some literatures[10,11] apply LM (Levenberg-Marquardt) algorithm which is used to solve non-linear least square problem instead of BP algorithm[12,13]. To improve the efficiency of LM algorithm, based on the special structure of error function of this problem, this paper creates a LM algorithm model which is appropriate to solve the problem about identification of weight parameters of multi-layered feedforward neural network[14-15]. Furthermore, give two applications in the petroleum production.

At present, most of the waterflooding exploitation oilfields in our country are in the late stage, how to enhance the oilfield production and improve the recovery ratio are critical issues[16,17]. The development plan which extracts the remaining oildepends on the distribution and type of the remaining oil. The main index which indicates the distribution of the remaining oil is the oil saturation[18]. In fact, to detect the remaining oil in the oil-bearing stratum, the only effective method is to measure the resistivity of the stratum because of being difficult to measure oil saturation directly. That's why we study the relationship between resistivity of the stratum and oil saturation. This paper bases on the neural network to set up a mathematical model about the relationship. The method is used to model the nonlinear mathematical model of the functional relationship between the resistivity and oil saturation of the stratum in the ASP (Alkali Surfactant Polymer) complicated flooding systems. The result research indicates that the algorithm has fast convergence and high precision.

In the many investment projects of the oilfields, the relationship between investment and its maximum income, and relationship of anticipative income and its minimum investment is not linear relationship. Under

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the condition of given investment cost, we created a mathematical model of maximum income calculated by investment cost. We got the investment saturation point by the simulation function of neural networks model, studied the income growth rates using its well analysis characteristic.

2 Simplification of feedforward neural networks model

We gave a simplified mode of feedforward neural networks, which is adaptive to use LM learning algorithm to train the weights of neural network.

Suppose that M input-output data pairs $(\boldsymbol{x}_m, \boldsymbol{y}_m)$, $m=1,2,...,M$ are obtained from a nonlinear dynamic system, where $\boldsymbol{x}_m = [x_{1,m},...,x_{i,m},...,x_{I,m}]^T$ and $\boldsymbol{x}_{I,m}=1$, $\boldsymbol{y}_m=[y_{1,m},...,y_{k,m},...,y_{K,m}]^T$. It is proved that for such a dynamic system, if only the mapping is a continuous function, it can be arbitrarily well approximated by a feedforward network with only a single internal hidden layer: $f_{NN}: R^I \to R^K$ and

$$\hat{\boldsymbol{y}}_m = f_{NN}(\boldsymbol{x}_m, \boldsymbol{v}, \boldsymbol{w}) \quad (1)$$

Where $\boldsymbol{v}$ is a vector arranged by the elements v_{ij}: $i=1,2,...,I; j=1,2,...,J-1$ (In fact, it is a column spread vector of weights matrix, which is called weights vector in the following) connecting nodes of the input layer and those of the hidden layer, $\boldsymbol{w}$ is a vector arranged by the elements w_{jk}: $j=1,2,...,J; k=1,2,...,K$, which is weight vector connecting nodes of the hidden layer and those of the output layer. Our target is that through adjusting weights vectors $\boldsymbol{v}, \boldsymbol{w}$ to make the outputs of the network model $\hat{\boldsymbol{y}}_m$ approaching the outputs of the system $\boldsymbol{y}_m$. The expression of neural network model (1) is given. Set the input of the hidden layer is

$$\bar{h}_{jm} = \sum_{i=1}^{I} v_{ij} x_{im}, j=1,2,...,J-1 \quad (2)$$

Set the output of the hidden layer is

$$\hat{h}_{jm} = g(\bar{h}_{jm}),\ j=1,2,...,J-1 \text{ and } \hat{h}_{Jm}=1 \quad (3)$$

Let

$$\hat{y}_{km} = \sum_{j=1}^{J} w_{jk} \hat{h}_{jm},$$

$$k=1,2,...,K, \text{ where } \hat{h}_{Jm}=1 \quad (4)$$

From Eq. (2) ~ (4) and $\hat{\boldsymbol{y}}_m = [\hat{y}_{1,m},...,\hat{y}_{k,m},...,\hat{y}_{K,m}]^T$, get the expression of Eq. (1).

3 Weights parameter identification model that adapted to apply LM method

As we all know that the gradient descent method converges fast when still a long distance from the minimum, but the method will zigzag to make the objective function descent slowly when approaching the optimal solution. For Newton method, a better direction of search will yield only when the objective function approaches the optimal solution. And LM method is the combination of the gradient descent method and Newton method.

Obviously, from (1) ~ (4), $\hat{y}_{km}$ is the function of $\boldsymbol{x}_m, \boldsymbol{v}, \boldsymbol{w}$. Let $\boldsymbol{u}=[\boldsymbol{v}^T, \boldsymbol{w}^T]^T$, we can get $\hat{y}_{km} = \hat{y}_{km}(\boldsymbol{x}_m, \boldsymbol{u})$. When we discuss identification algorithm of the weight vector $\boldsymbol{u}$, $\hat{y}_{km} = \hat{y}_{km}(\boldsymbol{u})$ is expressed simply.

The weights learning of the multi-layered feedforward neural network is in fact an unconstrained optimization process. The objective function is the sum of the square of the error, i. e.

$$\min_u E(\boldsymbol{u}) = \frac{1}{2}\sum_{m=1}^{M}\sum_{k=1}^{K}(y_{km} - \hat{y}_{km}(\boldsymbol{u}))^2 = \frac{1}{2}\sum_{k=1}^{K} e_k^T(\boldsymbol{u}) \cdot \boldsymbol{e}_k(\boldsymbol{u}) \quad (5)$$

Where error vector

$\boldsymbol{e}_k(\boldsymbol{u}) = [e_{k1}, e_{k2}, ..., e_{kM}]^T$, and that $e_{km} = y_{km} - \hat{y}_{km}(\boldsymbol{u})$, $k=1,2,...,K$

$$m=1,2,...,M \quad (6)$$

As stated above, $\hat{y}_{km}(\boldsymbol{u})$ is the function of weights $\boldsymbol{u}$ and input value $\boldsymbol{x}_m$. When $\boldsymbol{u}$ is given, network output value $\hat{y}_{km}(\boldsymbol{u})$ of input vector $\boldsymbol{x}_m$ of No. m can be calculated by network structure, and y_{km} is its output expectation value.

For each output point k, can are given LM algorithm corresponding to

$$e_k = \frac{1}{2}\boldsymbol{e}_k^T(\boldsymbol{u}) \cdot \boldsymbol{e}_k(\boldsymbol{u}), k=1,2,...,K \quad (7)$$

And then present algorithm of problem (5).

Assume initial value of $\boldsymbol{u}$ is $\boldsymbol{u}^0$ (e. g., pseudo-random number in interval [0, 1] can be weight initial value). Generally, set n as iteration times, we linearize e_{km} in the Eq. (6) at $\boldsymbol{u}^n$, get

$$e_{km}(\boldsymbol{u}) \approx e_{km}(\boldsymbol{u}^n) + \nabla e_{km}(\boldsymbol{u}^n)^T(\boldsymbol{u}-\boldsymbol{u}^n) \quad (8)$$

From Eq. (6), be able to get vector mode of (8)

$$e_k(\boldsymbol{u}) \approx e_k(\boldsymbol{u}^n) + J_k(\boldsymbol{u}^n)(\boldsymbol{u}-\boldsymbol{u}^n),$$

$$k=1,2,...,K \quad (9)$$

Where $J_k(\boldsymbol{u})$ is Jacobian matrix of $e_k(\boldsymbol{u})$, viz., No. m row of $J_k(\boldsymbol{u})$ is $\nabla e_{km}(\boldsymbol{u})^T, m=1,2,...,M$

Using (9), then minimization problem of (7) becomes minimization problem of

$$e_k \approx \frac{1}{2}\| e_k(\boldsymbol{u}^n) + J_k(\boldsymbol{u}^n)(\boldsymbol{u}-\boldsymbol{u}^n)\|_2^2,$$

$$k=1,2,...,K$$

Therefore, get its standard equation, which is

$$J_k(\boldsymbol{u}^n)^T J_k(\boldsymbol{u}^n)(\boldsymbol{u}-\boldsymbol{u}^n) = -J_k(\boldsymbol{u}^n)^T e_k(\boldsymbol{u}^n),$$

$$k=1,2,...,K$$

Marks

$$G_n = \sum_{k=1}^{K} J_k(\boldsymbol{u}^n)^T J_k(\boldsymbol{u}^n),\ \boldsymbol{g}_n = \sum_{k=1}^{K} J_k(\boldsymbol{u}^n)^T e_k(\boldsymbol{u}^n)$$

Under G_n is reversible, we can get $\boldsymbol{u}$, and set $\boldsymbol{u}$ as $\boldsymbol{u}^{n+1}$, get

$$\boldsymbol{u}^{n+1} = \boldsymbol{u}^{n} - G_n^{-1}\boldsymbol{g}_n, n = 0,1,2,\ldots. \quad (10)$$

This is the iteration method mode of Gauss-Newton method.

G_n maybe singular, but should be semi-positive definite, so, for any positive number β_n and identity matrix $\boldsymbol{I}$ whose order is same as order of G_n, $G_n + \beta_n \boldsymbol{I}$ must be reversible. Therefore, the iteration method (10) which calculated $\boldsymbol{u}$ can be modified as

$$\boldsymbol{u}^{n+1} = \boldsymbol{u}^{n} - (G_n + \beta_n \boldsymbol{I})^{-1}\boldsymbol{g}_n, n = 0,1,2,\cdots \quad (11)$$

This is LM method to solve optimum weight vector problem. When using LM method, set weights of the neural network to the initial value $\boldsymbol{u}^0$, and set the LM factor β to the initial value $\beta_0 > 0$. Let $\alpha > 1$ be amplification coefficient of β; and let $\alpha_1 : 0 < \alpha_1 < 1$ be minification of β, set control precision of the gradient modulus $\varepsilon > 0$. Set $\boldsymbol{I}$ as identity matrix whose order is same as G'_s during iteration, when let $\alpha\beta \Rightarrow \beta$, can increase weight β of the gradient descent method to make algorithm to converge. On the other side, when let $\alpha_1\beta \Rightarrow \beta$, can increase weight $1/\beta$ of Newton method to enhance the speed of convergence.

In the actual calculation, also according to Eq (11), set $\boldsymbol{p}_n = (G_n + \beta \boldsymbol{I})^{-1}\boldsymbol{g}_n$ at the No. n iteration, make one dimension search along direction $\boldsymbol{p}_n$, get its step length η by quadratic interpolation method. Set calculated optimum step length to η_n, Eq (11) should be modified to

$$\boldsymbol{u}^{n+1} = \boldsymbol{u}^{n} + \eta_n \boldsymbol{p}_n, n = 0,1,2,\ldots \quad (12)$$

The following give two applications of Neural-net-based Modeling in the Petroleum Production. In the emulational calculation, I-J-K: 2-4-1, 2-5-1, 2-6-1 was ever used network structure respectively. The data of this paper employs 2-6-1 network structure.

4 Application in modeling of ASP complicated flood system

When exploitation the oil field in the late stage of development, in order to map the distribution of the remaining oil in oil-bearing strata, we must study the main index—oil saturation, which indicates the distribution of the remaining oil. But it is difficult to measure the remaining oil saturation directly, so we can only do it through measuring the resistivity of the strata[19]. The effective method is to study the relationship between resistivity and oil saturation, and set up the mathematical model.

The electrical property of rock is determined by petrophysical property, permeability, water and oil saturation, mineralization ratio of the water in the strata and temperature, etc. We study the relationship between the resistivity and the oil saturation in the whole procedure of waterflooding, polymeric compound flood and ASP complicated flood, provided the invariable petrophysical property, permeability, mineralization ratio and temperature. Using the long man-made one dimension cores with the size (2 cm × 2 cm × 30 cm) to do the displacement experiments of waterflooding, polymeric compound flood and ASP complicated flood. The permeability of these cores are 500, 1000, 2000 millidarcy respectively. Study the relationship between resistivity and oil saturation through the variation of the resistivity detected by data select system. Through analyzing the input and output data, we can set up the mathematical model of the relationship between resistivity and oil saturation. This is a non-linear mathematical model.

We adopt a multi-layer feedforward network for modeling, and apply LM algorithm for the weights training. Adopting 2-6-1 structure, the inputs is $\boldsymbol{x}_m = [x_{1m}, x_{2m}]^{\mathrm{T}}$ ($x_{2m} = 1, m = 1,2,\ldots,M$), where x_{1m} is resistance R(kΩ), the outputs y_m ($m = 1,2,\ldots,M$) represents oil saturation (%). Set an example of the permeability—2000 millidarcy, samples of ($\boldsymbol{x}_m, \boldsymbol{y}_m$), $m = 1,2,\ldots,M$ is obtained in the laboratory. Train the network with the algorithm as stated above.

The result of the weights training is shown in Table 1:

Table 1 The training result of weights

v_{11}	v_{12}	v_{13}	v_{14}	v_{15}	v_{21}	v_{22}	v_{23}	v_{24}	v_{25}	w_1	w_2	w_3	w_4	w_5	w_6
-7.687	0.5747	60.53	-4.145	2.095	20.10	-4.065	-322.9	-3.929	4.1993	-5.559	44.14	13.52	24.50	0.0864	22.42

The model has higher accuracy, except one point, most of the accuracy can reach 99 %, few is not below 96 %, Fig. 1 shows the system and model response, x axis represents resistance R(kΩ), y axis represents oil saturation (%). In the figure, the point is the data actually measured; the solid line response the output of the neural network model.

Applying the mathematical model, we can set up the functional relationship between strata resistivity and oil saturation under the condition of invariable petrophysical property, permeability, mineralization ratio of the water in the strata and temperature. Then through measuring the resistivity of each point in the oil-bearing strata, we can estimate the oil saturation.

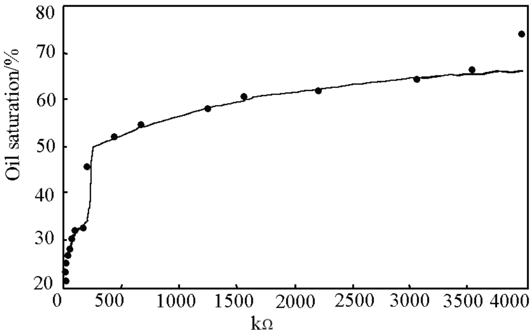

Fig. 1　Curves of system and model response

5　The application of neural-NET-based modeling in the system of relationship between investment and income

Suppose that the number of No. i item is x_i and the investment cost is q_i (10^4 yuan), $i = 1, 2, \ldots, n$, which annual income is r_i (10^4 yuan), $i = 1, 2, \ldots, n$ among n projects. To figure the reliability and stability index of investment income data, set risk loss index of income to $k_i, i = 1, 2, \ldots, n, (0 < k_i < 1)$. Therefore, expected value considered risk loss is $k_i r_i x_i$ (10^4 yuan), $i = 1, 2, \ldots, n$. Suppose that the receivable maximum risk loss of one item is ρ times ($0 < \rho < 1$) of total anticipative income, namely, $\max\{k_1 r_1 x_1, \ldots, k_n r_n x_n\} \leqslant \rho(\sum_{i=1}^{n} x_i r_i)$. Suppose that the total number of investment i tems is n_p, and the test item number of No. i item is a_i. So, we can get Investment-Income Model as following:

$$\max R = \sum_{i=1}^{n} x_i r_i \qquad (13a)$$

$$s.t.\begin{cases} x_1 + x_2 + \cdots x_n = n_p, (\text{Total items limite}) \\ x_1 q_1 + x_2 q_2 + \cdots + x_n q_n \leqslant Q, (\text{Total investment cost limited}) \\ x_i \geqslant a_i, i = 1, 2, \ldots, n, (\text{Test item number limited}) \\ \max\{k_1 r_1 x_1, k_2 r_2 x_2, \ldots, k_n r_n x_n\} \leqslant \rho \sum_{i=1}^{n} r_i x_i, (\text{Receivable risk limited}) \\ x_1, x_2, \ldots, x_n \text{ all is integer} \end{cases} \qquad (13b)$$

To $n_p = 1870$, then $n = 9$, set the value to a_i, q_i, r_i as Table 2 shows.

Table 2　The values of a_i, q_i, r_i

i	1	2	3	4	5	6	7	8	9
a_i	0	0	0	0	0	0	0	0	0
$q_i/10^4$yuan	9.5	18	0.8	0.7	0.6	0.25	0.08	1.5	1.4
$r_i/10^4$yuan	0.84	2.28	0.57	1.95	1.89	0.758	0.258	2.94	2.67

Set $Q = 200, 400, \ldots, 5\,000$ (10^4 yuan) in turn, using model (13). To highlight this paper's subject, we simply k_i, set each k_i, equal to k, namely, the risk of each investment project is close, or reliability of each r_i is similar. So, we can set risk index $fxs = k/\rho$. If set risk index $fxs = 3$, we get curve of investment cost x vs. income y which is dot-dash curve on the upper part of Fig. 2; If set risk index $fxs = 5$, get curve of investment cost x vs. income y which is dot-dash curve on the lower part of Fig. 2.

We solved 2-6-1 neural network model weight value as Table 3 shows using array $x \rightarrow y$ which is corresponded to dash line in Fig. 2 under the condition of $fxs = 3$.

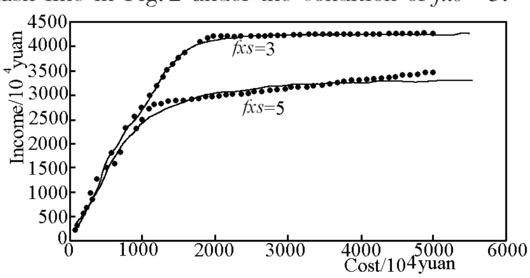

Fig. 2　Curve of investment cost x vs. income y

Using the data of Table 3, we get solid curve of $fxs = 3$ as Fig. 2 shows, namely, it is simulation curve of neural network model. Analogously, we can get the other solid curve in the Fig. 2.

Because the neural network model function which we applied has derivative of arbitrary order, we can get curve of investment cost x vs. income rate θ (Fig. 3).

Table 3　The training result of weights

v_{11}	v_{12}	v_{13}	v_{14}	v_{15}	v_{21}	v_{22}	v_{23}	v_{24}	v_{25}	w_1	w_2	w_3	w_4	w_5	w_6
−9.447	6.984	−17.45	−4.190	2.513	19.74	−49.96	−60.73	−3.938	−15.70	−5.489	1369	1453	2.447	2572	322.6

In the curve of investment cost x vs. income rate θ, x-coordinate is investment cost, y-coordinate is the growth rate of annual income. Fig. 3 shows that when investment is 450 (10^4 yuan), the growth rate of income is maximum, at this time, once add a unit investment, we can get 3.6 times return. Investment cost 2 500 (10^4 yuan) is the investment saturation point, at this time, added investment can't enhance the income.

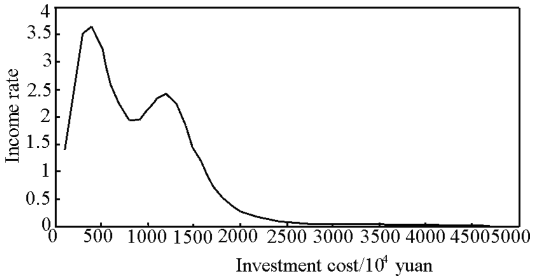

Fig. 3 Curve of investment cost x vs. income rate θ

When give a investment cost x, such as $x = 600$ (10^4 yuan), then set model (13) $Q = x$, if other data can be set, then we can solve model (13), and get a specific optimization investment solution.

6 Conclusions

The results show that modeling non-linear system with neural networks is an effective approach. Training weights with LM algorithm can obtain satisfied results within tens of steps, and the result is good with high precision. The difficulties of directly measuring the oil saturation could be solved by applying neural network to study the relationship between oil saturation and strata resistivity in the ASP complicated flooding system. And Investment-Income rate curve is able to bring good investment strategy intuitionally and also bring investment saturation point which should be avoided of. Above two examples proved this method has wide application prospect in the field of non-linear system identification.

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