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Forecast Groundwater Level for Management with Neural Network and Fuzzy sets

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ABSTRACT

This paper introduces a new model for forecasting groundwater level on the basis of analysing defect of finite element method. The new model is built with fuzzy sets and neural networks. It is convenient for use. We computed the groundwater level of one city in P. R. China with it and got a very satisfactory result. It can be popularized to corecast groundwater level of mine.

KEYWORDS: neural networks, fuzzy numbers, groundwater level corecast.

1. INTRODUCTION

The goverment of every big city must have a good plan of excavating to groundwater and managing it. The key of the plan is groundwater level corecast. So do big mine. Now the finit element method of partial differential equation is used usually. The problem of partial differential equation is

$$\frac{a}{ax}[k(h-B)\frac{ah}{ax}]+\frac{a}{ay}[k(h-B)\frac{ah}{ay}]+\varepsilon_1-\varepsilon_2-\sum_{W=1}^{m}Q_w\,\delta(x-x_w,y-y_w)-\mu\frac{ah}{at}=0,\quad (x,y)\in D,\ t>t_o$$

$$h(x,y,t)\big|_{t=t_o}=h_o(x,y),\quad (x,y)\in D$$

$$h(x,y,t)\big|_{\Gamma}=h_1(x,y,t),\quad (x,y)\in\Gamma,\ t>t_o$$

Where $h=h(x,y,t)$ —— groundwater level

k —— coefficient of pemeability

μ —— specific yield

In order to find out its numerical solution, first the k and μ must be computed with data of pumping test. The computing process is very long and difficult. It need one to two years with faster computer usually. Only by relying on the experts can we do our work well. General employee can not master the technique. And when the conditions of contributing region are changed, the new computing process is very long and difficult too. In order to surmount the above defets we introduced a new model of groundwater level corecast with neural networks and fuzzy numbers.

2. THE STRUCTURE OF NEURAL NETWORK

Because the conditions of contributing region and groundwater level are fuzzy, we use fuzzy numbers with membership functions

$$f(x)=\frac{1}{\sqrt{2\pi}\,\sigma}e^{-\frac{(x-h)^2}{2\sigma^2}}$$

to represent groundwater level. So every value of groundwater level corresponds two parameters h and σ. The process of calaulating parameter is similar. We showed how calculate h below.

The neural network for groundwater level corecast is shown in Fig.1,

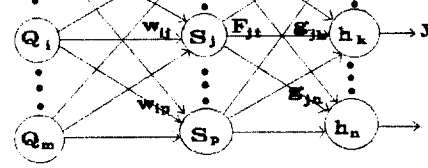


Fig. 1

where w_{ij} — the connection weight from the node Q_i in input layer to the S_j node in hidden layer.

g_{jk} — the connection weight between node S_j and h_k.

F_{jt} — export value of node S_j corresponding (t)th learning sample.

$\hat{y}_{kt}$ — calculating export value of node h_k corresponding (t)th learning sample.

There are N learning samples:

$X_t=(x_{1t},x_{2t},\cdots,x_{it},\cdots,x_{mt},1)$, $(t=1,2,\cdots,N)$.

Let y_{kt} be teacher's signal corresponding node h_k and learning sample X_t.

In the learning process of neural network, following formulas are used:

$$F_{jt}=\sum_{i=1}^{m+1} w_{ij}x_{it} \quad \cdots\cdots\cdots\cdots (1)$$

$$\hat{y}_{kt}=\sum_{j=1}^{p+1} g_{ij}F_{it} \quad \cdots\cdots\cdots\cdots (2)$$

where $w_{m+1j}=-\theta_j$, $g_{p+1k}=-\eta_k$, $F_{p+1t}=1$,

θ_j — threshold value of node S_j,

η_k — threshold value of node h_k;

$$g_{jk}(c+1)=g_{jk}(c)+\mu_2\sum_{t=1}^{N}(y_{kt}-\hat{y}_{kt})f_2'(met_{kt})F_{jt} \quad \cdots\cdots (3)$$

where $met_{kt}=\sum_{j=1}^{p+1} g_{jk}F_{jt}$, μ_2 is control coefficient,

$$w_{ij}(c+1)=w_{ij}(c)+\mu_1\sum_{t=1}^{N}\{[\sum_{t=1}^{n}(y_{kt}-\hat{y}_{kt})f_2'(met_{kt})g_{jk}]\cdot f_1'(net_{jt})\cdot x_{it} \quad \cdots\cdots (4)$$

where $net_{jt}=\sum_{i=1}^{m+1} w_{ij}x_{it}$, μ_1 is control coefficient.

We took there practical moves to raise the convergence rate in learning process.

First, there is one threshold θ for all nodes in all layers usually. In our model, different node has different threshold. They are shown above $S_j\rightarrow\theta_j$, $h_k\rightarrow\eta_k$.

Second, we set up different correction coeficient and output function for corresponding layer.

Third, in the formula (4)

$$[(y_{kt}-\hat{y}_{kt})f_2'(met_{kt})g_{jk}]$$
$$=[y_{kt}(c+\tfrac{1}{2})-\hat{y}_{kt}(c+\tfrac{1}{2})f_2'(met_{kt}(c+\tfrac{1}{2}))g_{jk}(c+1)]$$
$$\neq[y_{kt}(c)-\hat{y}_{kt}(c)]f_2'(met_{kt}(c))g_{jk}(c)$$

where $y_{kt}(c+\frac{1}{2})$, $\hat{y}_{kt}(c+\frac{1}{2})$, $met_{kt}(c+\frac{1}{2})$ are calculated with $g_{jk}(c+1)$ and $w_{ij}(c)$, $y_{kt}(c)$, $\hat{y}_{kt}(c)$, $met_{kt}(c)$ are calculated with $g_{jk}(c)$ and $w_{ij}(c)$.

3. RESULT AND DISCUSSION

We apply the neural network in section 2 to calculating groundwater level of ** city in hebei province. There

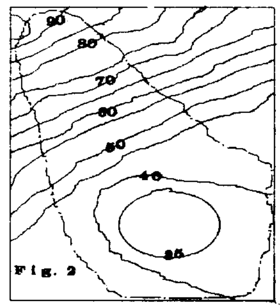
Qi corresponding to ith pump discharge,

hk corresponding to groundwater lever of kth observation well.

Data and program are omitted because these must be keep secret. We showed a map in Fig.2. It is drawn with calculated data.

Practice proves that the degree of accuracy of the model is over ninety percent. It is higher for supply system.

a map of groundwater level ** city, 1992



—·— is the boundary line of management water area of ** city.

It is a important problem to raise the convergence rate yet. There are more ten thousands times learning in our computing.

In order to raise the degree of accuracy, we have to improve the numbers of node in input lager and output layer. It will lead to more times of learning. We hope to see better research result.

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