A Hybrid Model for Soil Moisture Prediction by Using Artificial Neural Networks

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Abstract
Accurate prediction of soil moisture time series plays an important role in guiding agricultural production. Used a hybrid method which combine discrete wavelet decomposition (DWT), BP neural network and particle swarm optimization (PSO) to predict the time series of soil moisture data obtained from wireless sensor networks. Meanwhile aimed at the limitations of BP and PSO, we proposed corresponding improved algorithm. Carried out experiment in Kenli town, the research region of "Bohai granary" in ShanDong province, results showed that our method has higher predicting accuracy and convergence speed.

Keywords: PSO, BP, Wavelet Transform, Soil Moisture

1. INTRODUCTION
Soil moisture is an important parameter in the study of land surface process. As the main carrier of soil mass transport and biological chemistry, soil moisture is one of the most important factors that affect the growth of crops. So accurate prediction of soil moisture is of great significance to agricultural production.

With the development of wireless sensor networks, it has been widely used in the field of soil moisture measurement. By using wireless sensor networks, soil moisture time series can be obtained, which provides a high quality data source for the prediction of soil moisture. There are two kinds of time series prediction methods, statistical methods and artificial intelligence methods. Statistical prediction model uses historical data to reveal the correlation between the data, and use this association to complete the prediction. Erdem E et al. (2011) used ARMA to predict wind speed and direction. Tascikaraoglu A et al. (2014) respectively used AR, ARIMA to predict time series. Experiment results found than when there is a linear correlation between the time series, the statistical prediction model will get better results. But soil moisture is a nonlinear time series, it is difficult to obtain ideal prediction results by using statistical models.

Compared with the statistical model, the artificial intelligence prediction method is more suitable for nonlinear time series. S.L.HO et al (2002) compared artificial intelligence prediction method with statistical methods, results show that artificial intelligence model has better predicting accuracy when the time series is random distribution and nonlinear. Gan-qiong Li et al (2010) used feed-forward ANN to predict time series, results show that feed-forward ANN has better predicting accuracy than ARIMA. Meanwhile, wavelet decomposition is used to predict time series, Anbo Meng et al (2016), Jianming Hu et al (2015) used wavelet decomposition to decompose original time series into subseries, then used artificial neural networks to predict each subseries, results show that this kind of algorithm has faster training speed and higher predicting accuracy.

BP neural network is a typical artificial neural network, which has good nonlinear mapping ability and is widely used in the predicting of time series. Haoxiong Yang (2012) used BP to predict time series and obtained good results. The predicting accuracy and training time of BP often depends on the initial weights and thresholds, which are set to a random value in standard BP. Heuristic algorithms are used to optimize the initial weights and threshold of BP. Liang GM et al. (2013) and A.U. Haque et al. (2015) use heuristic algorithms to optimize the initial weights and threshold of BP, then use improved BP to predict time series, results show that these improved algorithm has faster training speed and higher predicting accuracy.

In this paper, prompt a hybrid method which combine wavelet decomposition, BP neural network and PSO together to prediction soil moisture time series. Experiments are carried out used soil moisture time series obtained from 10 observation stations in Kenli County, Dongying City, Shandong Province. By applying different prediction methods to the same set of time series, demonstrate the effectiveness of the method proposed in the paper.

2. GENERAL SITUATION OF EXPERIMENT AREA

In 2013 China launched the “Bohai granary” technology demonstration project, through the transformation of the Bohai area of about 4000000 acres of low yielding fields and about 10000000 acres of saline wasteland, achieve growth to 6 billion kg of grain in 2017, 10 billion kg of grain in 2020. “Bohai granary” Shandong project area mainly involves 3 cities : Dezhou, Dongying, Binzhou. The experiment area is located in the...
territory of Kenli County, Dongying City. Fig.1 displays Shandong projection area of “Bohai granary”, the position of experiment area is showed in black box.

There are 10 monitoring stations in the experiment area which collect hourly soil moisture data. Fig.2 shows the distribution of the 10 monitoring stations. Select time series data from 1 January 2013 to 31 December 2014 (total 17520*10 data), use arithmetic mean of data at the same time point from these 10 monitoring stations as the original experiment data(17520*1 data).Fig.3 illustrate the distribution of original time series, the value of which is between 0.15 to 0.63.

3. THE HYBRID DWT-IPSO-IBP ALGORITHM

3.1. Discrete wavelet decomposition

As soil moisture time series is characterized by high autocorrelation and inherent volatility, use DWT to decompose original time series into subseries of relatively stable, then use BP to predict subseries, finally gain the prediction result by means of the wavelet reconstruction technique. Fig.4 illustrate the procedure of prediction.
According to the selection method of wavelet function proposed by Yanfang Sang et al.(2008), use db3 to do the DWT. Fig 5 shows the decomposition result, in which the wavelet decomposition level is 8, “s” represent the original time series.

Each subseries has different distribution characteristics, according to this feature use BP neural networks with different structures to predict each subseries respectively. The framework of the proposed prediction approach is illustrated in Fig.6. The main procedure for prediction can be described as below:

1) Determine the parameters of BP networks.
2) Use IPSO to improve the initial weight and threshold of BP.
3) Use IBP to predict each subseries.
4) Use the wavelet reconstruction to obtain the final prediction result.

In this study we pick a 3-layer network, which include only 1 hidden layer. First according to Hui Liu et al.(2012) we use ACF and PACF to analyse each subseries, obtain the neuron number for input layer. Then according to Hecht–Nelson method which illustrate the relationship of neuron number between the input layer
and hidden layer determine the neuron number of hidden layer. For the neuron number of output we set 1 in this study.

3.3. Use improved PSO to optimize initial weight and threshold of BP

We choose PSO to optimize the the initial weight and threshold of BP, the step of which is as follows:
(1) encode initial weight and threshold as particle.
(2) calculate particle fitness value, update ibest and gbest.
(3) update location and speed according to particle fitness and number of iteration.
(4) Check if the termination condition is met, if met then gbest is the value we need, else repeat step 2.

In standard PSO location and speed is update using equations (1), (2):

\[ s_i(t+1) = os_i(t) + a_1(os_{ib} - l_i(t)) + a_2(os_{gb} - l_i(t)) \]

\[ l_i(t+1) = l_{ib}(t) + s_i(t+1) \]

Where \( s_i \) and \( l_i \) are velocity and position after the \((t+1)\) iteration; \( os_{ib} \) and \( os_{gb} \) are ibest and gbest which represent the individual and global optimal solution; \( a_1 \) and \( a_2 \) are the acceleration constant; \( \omega \) is inertia weight which is linear decreased in standard PSO (Equation (3)):

\[ \omega = \omega_{max} - \frac{\omega_{max} - \omega_{min}}{iter_{max}} * iter \]

Where \( \omega_{max} \) and \( \omega_{min} \) are initial and final value of inertia weight, \( iter \) is num of iteration, \( iter_{max} \) is maximum number of iterations. In this study we use fitness value and number of iteration together to update \( \omega \), \( a_1 \) and \( a_2 \), the step is as follow, in which \( a_{1p} \) and \( a_{2p} \) is constant:

(1) Calculate the fitness value of all particle.
(2) calculate the average of all the fitness value: \( f_A \)
(3) divide the particle into two group: if its fitness value \( f < f_A \), then it belongs to \( S \) group, else it belongs to \( B \) group.
(4) calculate the average fitness value of the two group: \( f_{AB}, f_{AS} \)
(5) use Equation (4) update \( \omega \), \( a_1 \) and \( a_2 \)

\[
\begin{align*}
\omega &= \omega_{max} \\
\omega &= \omega_{max} - (\omega_{max} - \omega_{min}) * \frac{iter}{iter_{max}} \\
\omega &= \omega_{max} - (\omega_{max} - \omega_{min}) * \frac{iter}{iter_{max}} \quad f \geq f_{AB} \\
\omega &= \omega_{max} - (\omega_{max} - \omega_{min}) * \frac{iter}{iter_{max}} \quad f_{AB} \leq f \leq f_{AS} \\
\omega &= \omega_{max} - (\omega_{max} - \omega_{min}) * \frac{iter}{iter_{max}} \quad f < f_{AS} \\
\omega &= \omega_{max} - (\omega_{max} - \omega_{min}) * \frac{iter}{iter_{max}} \quad f \leq f_{AS}
\end{align*}
\]

3.3. Use IBP to predict soil moisture time series

In standard BP, \( \omega \) is updated using equation (5):

\[ \omega_{ij}(t+1) = \omega_{ij}(t) + \Delta \omega_{ij}(t) \]

Where \( \Delta \omega_{ij} = - \frac{\partial E}{\partial \omega_{ij}} \eta (0 < \eta < 1) \) which called learning rate is constant in standard BP. Zhang ZX et al (2011) pointed out that constant \( \eta \) lead the problem of easy to fall into local optimal solution. In this study we use additional momentum method and adaptive learning rate method together to update \( \omega \):

\[ \omega_{ij}(t+1) = \omega_{ij}(t) + (1-\alpha) \eta \Delta \omega_{ij}(t) + \alpha \Delta \omega_{ij}(t-1) \]

Where \( \alpha \) is additional momentum factor, during training, \( \alpha \) and \( \eta \) can be adjusted according to different conditions.
4. EXPERIMENT RESULT

6 groups of comparative experiment are carried to demonstrate the effectiveness of DWT-IPSO-IBP. All of the 6 algorithms is illustrated in table 1.

<table>
<thead>
<tr>
<th>Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>BP</td>
<td>Used BP to predict soil moisture data</td>
</tr>
<tr>
<td>PSO-BP</td>
<td>Used particleswarm optimization and BP to predict soil moisture data</td>
</tr>
<tr>
<td>PSO-IBP</td>
<td>Used particleswarm optimization improved and BP to predict soil moisture data</td>
</tr>
<tr>
<td>IPSO-BP</td>
<td>Used improved particleswarm optimization and BP to predict soil moisture data</td>
</tr>
<tr>
<td>IPSO-IBP</td>
<td>Used improved particleswarm optimization and improved BP to predict soil moisture data</td>
</tr>
<tr>
<td>DWT-IPSO-IBP</td>
<td>Used DWT, improved particleswarm optimization and improved BP to predict soil moisture data</td>
</tr>
</tbody>
</table>

Table 1. 6 different algorithms

Fig. 7 illustrate predicted results of 6 algorithms, where horizontal axis is the number of iterations, vertical axis is the predicted results which is expressed by Mean Squared Error (MSE). For BP algorithm, the minimum MSE is 3.57E-05 at the 110th iteration, In the first 30 iterations MSE decrease rapidly, at the 55th and 80th iteration MSE obviously decreased. For PSO-BP, PSO-IBP, IPSO-BP, IPSO-IBP the MSE of which are significantly less than MSE of BP, which means these improved methods are effective for soil moisture prediction. For DWT-IPSO-IBP the minimum MSE is 1.003 E-10, which means this algorithm has the best prediction accuracy in all of the 6 algorithm.

Iterations numbers of 6 algorithms is illustrated in Fig. 8 BP run complete after 120 iterations. The minimum MSE of PSO-BP, PSO-IBP, IPSO-IBP are approximately the same (Fig. 7), but we can see from Fig. 8 that PSO-IBP and IPSO-IBP has significantly less iterations number than PSO-BP to reach to minimum MSE, which means PSO-IBP and IPSO-IBP can effectively reduce the iteration time. For IPSO-IBP the iteration number is 14, compare with it DWT-IPSO-IBP has the least iteration number which is 6. DWT-IPSO-IBP algorithm can significantly reduce the running time and improve prediction accuracy.

5. CONCLUSION

This paper proposed a soil moisture prediction algorithm DWT-IPSO-IBP which combine DWT, PSO and BP, meanwhile aimed at the limitations of PSO and BP proposed improve method for them.

The comparison of simulation result of BP, PSO-BP, PSO-IBP, IPSO-BP, IPSO-IBP, DWT-IPSO-IBP shows that DWT-IPSO-IBP algorithm has higher prediction accuracy and faster convergence speed.
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