An improved back propagation neural network prediction model for subsurface drip irrigation system

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A R T I C L E  I N F O

Article history:
Received 7 July 2016
Revised 13 February 2017
Accepted 13 February 2017
Available online 6 March 2017

MSC:
47H10
54H25

Keywords:
BP neural network
Genetic algorithm
Crop yield-irrigation model
Subsurface drip irrigation system

A B S T R A C T

A crop yield-irrigation water model, based on an improved genetic algorithm (GA)-back propagation (BP) neural network prediction algorithm, has been developed in this study. It mainly uses the improved BP neural network based on the GA algorithm to develop the yield-irrigation water model for predicting the corn yield for different irrigation systems under subsurface drip irrigation. The model with the GA-BP algorithm gives more accurate predictions of the yield. The average error is only 0.71%. The GA-BP algorithm also speeds up the convergence of the network, improves the accuracy of the prediction, and describes the relationship between the yield and irrigation water under subsurface drip irrigation more accurately. Hence, the model can be used to design irrigation systems under subsurface drip irrigation more accurately.

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1. Introduction

Subsurface drip irrigation (SDI) is one of the typical applications of micro-irrigation technology. It is a more efficient delivery system if water and nutrient applications are managed properly [1]. When it is under the low pressure condition, the water and nutrient can be supplied precisely to the root zone of the crops by embedding drip irrigation emitters in the active layer of the plant root system [2,3]. As there is little disturbance of the soil structure by SDI, it reduces the surface evaporation and deep seepage losses, eliminates surface runoff [4], and improves the efficiency of absorption of water and nutrients by the crops [5]. Therefore, SDI has been widely used on fruits, vegetables and other economic crops [6]. There are also pilot studies on the application of SDI on field crops.

However, to fully realize the water saving and yield increasing potential of SDI, it is necessary to develop a scientific SDI system [7–9]. The relationship between the crop yield and irrigation water can provide a quantitative basis for a reasonably optimized irrigation system [10,11]. However, the correlation between the crop yield and irrigation water is complex. Many studies have developed models between the crop and water based on limited irrigation experiments [11–13]. In these models, not only there are clear differences in the mathematical structures, but the expressions of the model parameters are also different. Although these models under certain conditions can meet the precision requirement of the yield forecast, however, due to the differences in the model structures and parameter expressions of the regional and time domain

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http://dx.doi.org/10.1016/j.compeleceng.2017.02.016
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characteristics, these models cannot be applied to other areas. Further, as the relationship between the crop yield and irrigation water is complex and nonlinear, and its mechanism is not clear, these are some of the limitations on the applications of these models.

Artificial neural networks (ANN), in particular, BP (back propagation) network model has the self-organizing, adaptive and self-learning function, with a strong ability to deal with nonlinear problems [14–16]. It is very propitious to recurrent changes and detect patterns in complex agronomic irrigation systems [17–19]. Neuro-Drip combines an ANN with a statistical description of the spatio-temporal distribution of the added water from a single drip emitter to provide easily accessible, rapid illustrations of the spatial and temporal subsurface wetting patterns [20]. Karasekřeter et al. (2013) used ANNs to develop a new system of irrigation ratios and time intervals, which achieved a 20.46% water saving and 23.9% energy saving [21]. Dursun (2014) used a soil moisture distribution map to develop an efficient improved photovoltaic irrigation system via the ANNs method. The system enabled the reduction of the orchards daily water and energy consumptions both by 38% [22]. However, there are shortcomings in the BP network model, such as trap in a local minimum and no convergence of shock [23]. Genetic algorithm (GA) is a calculation model which uses a global optimization search algorithm to mimic the natural biological evolution process, [24]. With the combination of BP neural networks and GA, it improves the BP learning training, optimize network power threshold, and promotes the rapid convergence and improves the efficiency and precision of the model [25]. In this study, an improved BP neural network prediction model based on GA has been used to develop the crop yield-irrigation water relationship model, which is to optimize a SDI system.

This paper is organized as follows. In Section 2, the yield-water model under SDI based on normal BP algorithm is introduced. In Section 3, the yield-water model under SDI based on GA-BP algorithm is discussed in details. In Section 4, the application and analysis of the yield-water model under SDI based on GA-BP algorithm model is described in details.

2. The yield-water model under SDI based on normal BP algorithm

2.1. Experiment design and data selection

2.1.1. Experiment design

The field experiment was conducted in Fuxin City (41°41N42°56E and 121°01E122°56E) in western Liaoning Province in China. It was conducted in 2014 at the Key Laboratory of Liaoning Water-Saving Agriculture. The location is in a warm temperate zone with hot summers and cold winters and experiences continental monsoons. The annual average temperature and sunshine are 7.2 °C and 2865.5 h, respectively.

A permanent rain shelter was constructed over the experimental plots to provide continuous protection from rain. A large plastic sheet was put on top of the roof of the rain shelter. This sheet was laid down to cover plots on rainy days and rolled up on sunny days, ensuring that conditions remained ecologically similar to the adjacent unsheltered field area.

In the experiments, the irrigation water has been set as one of the parameters, and the irrigation quota has been set at four levels. The field capacity used in the experiments are 50

2.1.2. Data selection

The relationship between the crop yield and water is nonlinear. At present, its mechanism is unclear. So, it is more suitable to use a BP neural network to develop the model. For the crops and water relationships, there is a variety of methods to describe the relationships. The most common methods describe the relationship between the ultimate yield and the irrigation water at each stage.

According to the growth characteristics of corn, its growth period can be divided into four stages, i.e. seedling stage, jointing stage, tasseling stage, and filling stage. The corn subsurface drip irrigation experiment was water treatment control in accordance with the jointing stage, tasseling stage and filling stage, and corn grain yield for economic yield. So, the input layer takes three neurons according to the three input variables corresponding to the irrigation at the three stages. The output layer takes one neuron according to one output variable corresponding to the yield of corn.

When the experiment was finished, the yield and the amount of irrigation water during the stage, tasseling stage, filling stage were analyzed statistically. Then, the next step was to develop the model. To make the network with good convergence and mapping capability, the following equation was used to normalize the data to [0, 1]:

$$x'_i = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}}$$  \hspace{1cm} (1)

Where $x_{\max}$ and $x_{\min}$ are the maximum and minimum of the irrigation amount or yield, $x_i$ is the sample, $x'_i$ is the normalized value.

2.2. Data modeling

The normal BP network model is a three or more layer neural network, which includes an input layer, a middle layer (hidden layer) and an output layer. The BP learning algorithm is essentially using a network error sum of squares as the objective function. It minimizes the objective function value according to the gradient method, i.e. using the gradient search technology to minimize the error of the mean square value between the actual output and the desired output of the network.
2.2.1. Initialization parameter set and convergence

The normal BP neural network uses the momentum gradient descent method as the network training method. The training function is traingdm. The momentum factor has been set to 0.8, the learning rate to 0.05, the maximum number of the training times to 10000, and the expected error is 0.001.

The model convergence calculation mainly uses the following mean square error (MSE) function as the optimization objective function:

\[ E = \frac{1}{N} \sum_{i=1}^{N} (y_i^d - y_i)^2 \]  \hspace{1cm} (2)

Where \( E \) is MSE, \( N \) is the number of samples, \( y_i^d \) is the ideal output, \( y_i \) is the actual output.

The model selects a set of input and target sample from the learning samples. The output and error are calculated through the transfer function and MSE function. The network converges until the network global error \( E \) is less than expected error. If the learning times are greater than the preset value, the network does not converge.

2.2.2. Model structure design

The yield-water model uses a three layer neural network, which includes an input layer, a middle layer (hidden layer), and an output layer. The input layer takes three neurons according to the three input variables, corresponding to the jointing stage, tasseling stage and filling stage. The output layer takes one neuron according to one yield variable. If the BP neural network input node is \( u \), the hidden layer nodes selected is \( 2u + 1 \), and the BP network model can well reflect the real [26]. So, the number of hidden layer nodes is seven. On this basis, the normal BP network model is using a three layer network. The structure is 3-7-1. The network diagram is shown in Fig. 1.

2.2.3. The determination of transfer function

In the model, the middle layer of the networks neurons transfer function is S-type tangent function using tansig. The output layer neuron transfer function is purelin.

3. The yield-water model under SDI based on GA-BP algorithm

For the BP neural network based on genetic algorithm (GA-BP), in the learning process of the BP neural network, the weight and threshold are described as chromosomes, an appropriate adaptation function is then selected to carry out the GA iteration until convergence. The flow chart of the GA-BP model is shown in Fig. 2.

The BP neural network initial weights are generated using the conventional approach, and optimized by the GA algorithm. The implementation steps are as follows:

1. Individual coding and population initialization

   The individual contains the whole weight and threshold value of the BP neural network. In this study, the individual code uses the real number coding method. The length coding is as follows:

   \[ S = n \times m + m \times l + m + l \]  \hspace{1cm} (3)

   Where \( m \) is hidden layer nodes, \( n \) is input layer nodes, \( l \) is output layer nodes.

   The population size to the global search function of GA has a great influence on the optimization effect. Therefore, it is necessary to use a population size that is appropriate to the problem in question. In this study, the size of the initial population is 50.
(2) Fitness function set and calculation
In order to use the GA to optimize the weight value, a fitness function is required to evaluate the individual. In the GA-BP model, the use of a fitness function \( f \) is based on the error of the output layer. The function \( f \) is defined as

\[
f = \frac{1}{1 + E}
\]  

(4)

After calculating \( f \), if the maximum number of iterations or the precision requirement is met, proceed to next step.

(3) Individual selection
The choice of individuals can be conducted according to the following probability value.

\[
p_i = \frac{f_i}{\sum_{i=1}^{k} f_i}
\]  

(5)

Where \( f_i \) is fitness value of individual \( i \), and \( k \) is number of individual species.

(4) Crossover operation and mutation operation

Instead of crossover or mutation operation, the best individual without crossover or mutation operation is the best individual directly copied into the next generation. For other individuals, it uses the crossover or mutation probability to generate two new individuals.

(5) Cyclic operation
Repeat Steps (2) \( \sim \) (4), until the training target meets the precision requirement or the maximum number of iterations to achieve the objectives set.

(6) GA-BP model development and prediction
After completing the genetic, the best individual of GA is taken as the initial weights of BP neural network. For a given sample data, the neural network is trained according to the BP algorithm, and the GA-BP model is developed. Then, the yield is predicted through the GA-BP model.
4. The application analysis of the model

The crop yield-irrigation water model, based on improved GA-BP neural network algorithm, has been applied to predict the corn yield during different irrigation system under SDI. In order to compare the GA algorithm to optimize results before and after training GA - BP neural network, the selection of some parameters with the normal BP neural network. The learning rate has been set to 0.05, the maximum number of training times to 10000, and the expected error is 0.001. The best individual trained by GA has been used to optimize weights and thresholds of the BP network. The input and output values based on the SDI experiment are shown in Table 1. The training samples are Nos. 1–9, and the test validation samples are Nos. 10–12.

After using GA to optimize the weights and threshold of the BP neural network, the model was trained, and thereafter, it carried out the predictions for Nos. 10–12 test validation samples. The comparison of the predicted and actual values is shown in Table 2. The simulation prediction results are shown in Fig. 3. From Table 1, it can be seen that the relative errors of the yield predictions for Nos.10–12 are less than 2%.

In order to compare the model optimized results based on the GA-BP algorithm and the normal BP algorithm, the crop yield-irrigation water model based on the normal BP neural network algorithm has been used to predict the corn yield during different irrigation system under SDI. Table 3 shows the prediction errors of the two models based on the GA-BP and BP neural networks.

The convergence speed of the two models are compared as follows. With the target error of 0.001, the training error of the BP neural network converges at the 4738th step, with the convergence 0.000999976. With the same target error of 0.001, the training error of the GA-BP neural network converges at the 2168th step, with the convergence 0.000999951. Hence, the convergence speed of the GA-BP neural network is faster than that of the normal BP neural network. Table 3 shows that the average relative error of the predictions by the GA-BP neural network is much smaller than that by the BP neural network.

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Table 1

The model input and output values.

<table>
<thead>
<tr>
<th>Number</th>
<th>Jointing stage</th>
<th>Tasseling stage</th>
<th>Filling stage</th>
<th>Output</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.02</td>
<td>0.05</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>2</td>
<td>0.05</td>
<td>0.00</td>
<td>0.05</td>
<td>0.37</td>
</tr>
<tr>
<td>3</td>
<td>0.00</td>
<td>0.08</td>
<td>0.06</td>
<td>0.39</td>
</tr>
<tr>
<td>4</td>
<td>0.43</td>
<td>0.01</td>
<td>0.13</td>
<td>0.23</td>
</tr>
<tr>
<td>5</td>
<td>0.32</td>
<td>0.50</td>
<td>0.19</td>
<td>0.55</td>
</tr>
<tr>
<td>6</td>
<td>0.09</td>
<td>0.31</td>
<td>0.26</td>
<td>0.48</td>
</tr>
<tr>
<td>7</td>
<td>0.94</td>
<td>0.48</td>
<td>0.40</td>
<td>0.67</td>
</tr>
<tr>
<td>8</td>
<td>0.47</td>
<td>0.56</td>
<td>0.64</td>
<td>0.84</td>
</tr>
<tr>
<td>9</td>
<td>0.52</td>
<td>0.59</td>
<td>0.51</td>
<td>0.62</td>
</tr>
<tr>
<td>10</td>
<td>1.00</td>
<td>1.00</td>
<td>0.86</td>
<td>1.00</td>
</tr>
<tr>
<td>11</td>
<td>0.81</td>
<td>0.73</td>
<td>0.81</td>
<td>0.74</td>
</tr>
<tr>
<td>12</td>
<td>0.87</td>
<td>0.54</td>
<td>1.00</td>
<td>0.96</td>
</tr>
</tbody>
</table>

Table 2

Model prediction result.

<table>
<thead>
<tr>
<th>Number</th>
<th>Actual value</th>
<th>Predicted value</th>
<th>Absolute error</th>
<th>Relative error</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>1.00</td>
<td>0.988</td>
<td>0.012</td>
<td>1.20</td>
</tr>
<tr>
<td>11</td>
<td>0.74</td>
<td>0.743</td>
<td>-0.003</td>
<td>1.62</td>
</tr>
<tr>
<td>12</td>
<td>0.96</td>
<td>0.954</td>
<td>0.006</td>
<td>0.62</td>
</tr>
</tbody>
</table>

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Fig. 3. Results of yield predictions by the GA-BP model.
Table 3
The prediction error of the two models.

<table>
<thead>
<tr>
<th>Model</th>
<th>Minimum relative error</th>
<th>Maximum relative error</th>
<th>Average relative error</th>
</tr>
</thead>
<tbody>
<tr>
<td>BP</td>
<td>1.29</td>
<td>4.20</td>
<td>2.47</td>
</tr>
<tr>
<td>GA-BP</td>
<td>0.20</td>
<td>1.62</td>
<td>0.71</td>
</tr>
</tbody>
</table>

Table 4
The irrigation schemes and yield prediction results.

<table>
<thead>
<tr>
<th>Number</th>
<th>Jointing stage</th>
<th>Tasseling stage</th>
<th>Filling stage</th>
<th>Yield</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>6.16 – 7.16</td>
<td>7.17 – 8.5</td>
<td>8.6 – 9.30</td>
<td>0.02</td>
</tr>
<tr>
<td>2</td>
<td>0.02</td>
<td>0.05</td>
<td>0.05</td>
<td>0.02</td>
</tr>
<tr>
<td>3</td>
<td>0.32</td>
<td>0.31</td>
<td>0.4</td>
<td>0.24</td>
</tr>
<tr>
<td>4</td>
<td>0.52</td>
<td>0.57</td>
<td>0.53</td>
<td>0.59</td>
</tr>
<tr>
<td>4</td>
<td>0.78</td>
<td>0.74</td>
<td>0.81</td>
<td>0.91</td>
</tr>
</tbody>
</table>

Therefore, the crop yield-irrigation water model based on the improved GA-BP neural network algorithm can speed up the convergence of the network, improve the accuracy of the prediction, and describe the relationship between the yield and irrigation under SDI more accurately.

Using the trained model, the different irrigation schemes of SDI system have been designed. Further, it is concluded that the irrigation system under different yield targets can be used to guide the agriculture production practice. The irrigation schemes and yield prediction results are shown in Table 4.

5. Conclusions

An improved BP neural network based on GA algorithm has been used to develop a crop yield-irrigation water model. The relative errors of the test sample outputs as compared to the target values are less than 2%. This is an indication that the developed model is effective.

The model has been used to predict the corn yield for different irrigation systems under SDI. The results show that the GA-BP model gives more accurate predictions of the yield. The average error is only 0.71%. The results show that the GA-BP model is better than the normal BP model in the convergence speed and the prediction error. The GA-BP model therefore describes the relationship between the yield and irrigation under SDI more accurately.

The relationship between the crop yield and irrigation water is nonlinear. The crop yield-irrigation water model based on the improved GA-BP neural network prediction algorithm can describe the relationship between the yield and irrigation under SDI system more accurately, which can be used to design irrigation systems under SDI more accurately.

Since the experimental data series is relatively short, there is no additional information on the predicted results for the test. Further, as the other factors of the yield which are the input parameters to the prediction model have not been studied, yet they may have an effect on the versatility of the model. Therefore, further study on these parameters is recommended.

Acknowledgements

The authors would like to express their sincere thanks to the editor and the anonymous reviewer for their comments and suggestions which have helped to improve this paper. This research was supported by the Special Fund for Agro-scientific Research in the Public Interest (grant no.201303125), the National Major Technology Program (grant no.2013BAD05B07; 2011BAD16B12; 2012BAD04B03) and the science and technology research projects of Liaoning province (grant no.2015103018).

Supplementary material

Supplementary material associated with this article can be found, in the online version, at 10.1016/j.compeleceng.2017.02.016.

References


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