# The Water Deficits Prediction of SC and NC by Bayesian Network

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Keywords: Bayesian network, Water deficits, Prediction.

**Abstract.** In order to predict the water situation in 15 years, this paper develops Bayesian Artificial neural network system. The directed cyclic graph is built and the conditional probability tables are calculated. It represents the relationships among variable nodes in the graph. The Bayesian network makes the prediction error of Artificial neural network smaller, which relies on the probabilistic inference. This paper predicts the water demand, water supply and value of water consumption in several critical indicators The final prediction results show that the water deficits of South Carolina and North Carolina have an ease .The total water deficit presented a decreasing trend from 1081.51 to 467.62 million tons, which proves the effectiveness of the intervention plan.

### 1. Introduction

Some research previous mainly focused on the water purification and conservation. Many people try to solve the problem of the water shortage by developing water-saving plan which is combined with the population growth models[1,2]. The innovation of this paper is the combination of the distribution of the water resources and the economical and geography factors, which makes the consideration more comprehensive.

In solving the optimization allocation of water resources and the forecast problem of the ownership of water resources in 15 years. Predecessors did a lot of work in building the water resources allocation model. Aimed at the poor water issue in the United States, they have established a corresponding analysis model to divide the America into several parts, which depends on the richness of water resources. Research shows that some mathematical experts have predicted the amount of water in fifteen years by BP networks[3]. They have also set the best transport and storage plan of this region, which have taken the distance and economic factors into the consideration.

### 2. Bayesian Artificial neural network system

### 2.1 The introduction of the Bayesian Artificial neural network

Bayesian networks have demonstrated to be a tool which is able to respond to the water framework directive requirements in water management:

•Taking into account the hydro-logical system, the social-economic and the environmental dimensions, as well as all the aspects involved with the overall water use in the basin.

•The need to involve users and stakeholders in the resource management and to increase public participation.

With neural networks, the main difficulty in mode building is controlling the complexity of the model and lack of tools for analyzing the results, such as confidence interval. However, Bayesian approach can handle such problem by defining vague prior for the hyper-parameters that determine the model complexity. And the Bayesian analysis yields posterior predictive distributions for any variables of interest, making the computation of confidence intervals possible. Prior knowledge about the model parameters can be incorporated in Bayesian inference and combined with training, data to control complexity of different parts of the model. Markov chain Monte Carlo method is applied to optimize the model control parameters and obtain the predictive distribution. The Bayesian neural network method is studied and used in the drift modeling for gyroscopes. Results show that the Bayesian neural network can produce better modeling and predictive performance.

### 2.2 Model establishing and solving

Calculating steps

After determining a good model and the guide data, and measuring the sample data information are combined, according to Bayesian rule, we can get parameters of the posterior distribution.  $p(\theta | D) \sim L(\theta | D)p(\theta)^{[3]}$  (1)

Where the  $\theta$  stands for all the parameters.

Where the  $L(\theta | D)$  stands for the Likelihood function.

According to the optimal estimation principle of the model, the prediction of a new input can be obtained by predict the distribution of the posteriors value.

$$\hat{y}^{new} = E\left[y^{new} \mid x^{new}, D\right] = \int f\left(x^{new}, \theta\right) p\left(\theta \mid D\right) d\theta \qquad (2)$$

Where the stands for the mathematical expectation of the posterior distribution.

Therefore we need some parameter approximation method or with the aid of numerical approximation method. Here, we use Markov chain Monte Carlo method (MCMC) to solve this problem. That consideration make the Bayesian Artificial neural network system more accurate and powerful.

• The directed cyclic graph <sup>[4]</sup>

The main principle of the Bayesian method is under the condition of the given data samples all unknown variables in the model to establish a probability distribution[5]. According to the established Bayesian network's variable, the state of the variables and the correlation relationship between them. Our directed cyclic graph is drawn to describe the uncertainty relationship between the variables.



Fig.1 Bayesian artificial network system(DAG)

| type                          | describe  | Va                | state      |          |  |
|-------------------------------|---|-------------------|------------|----------|--|
|                               |   |                   |            | 45000    |  |
| decision variables            | Measures required<br>to achieve goal  | C                 | 50000      |          |  |
|                               | C   |                   |            | 55000    |  |
|                               |   | $C_2$             | 3-5        |          |  |
|                               |   |                   | 5-7        |          |  |
|                               |   |                   | 0-100      |          |  |
| State variables               | The variables that<br>Contact the target<br>variables and<br>decision variables | $C_7 n$           | 100-200    |          |  |
|                               |   |                   | >200       |          |  |
|                               |   | $C_3 / km^2$      |            | 100-500  |  |
|                               |   |                   |            | 500-1000 |  |
|                               |   |                   |            | >1000    |  |
|                               | Table 2 Conditional prob  | ability in instar | ice system |          |  |
|                               |   | $C_1 / (km^2)$    |            |          |  |
|                               |   | 45000             | 50000      | 55000    |  |
| P(C4)/hundred million<br>tons | 0.8-1   | 0.45              | 0.41       | 0.39     |  |
|                               | 1-1.2   | 0.32              | 0.34       | 0.36     |  |
| P(C6)                         | 1.2-1.4   | 0.23              | 0.25       | 0.25     |  |
|                               | Low   | 0.57              | 0.47       | 0.38     |  |
|                               | Medium  | 0.28              | 0.32       | 0.37     |  |
| D(C5)/hundred million         | High  | 0.15              | 0.21       | 0.25     |  |
| P(C5)/hundred million<br>tons | 0.7-1   | 0.48              | 0.44       | 0.41     |  |
|                               | 1-1.3   | 0.29              | 0.32       | 0.34     |  |
|                               | 1.3-1.6   | 0.23              | 0.24       | 0.25     |  |
|                               |   |                   |            |          |  |
| P(C8)                         | Low   | 0.34              | 0.29       | 0.21     |  |

| Table 1 | Bayesian | network | variables | in 1 | the | instance | system |
|---------|----------|---------|-----------|------|-----|----------|--------|
|---------|----------|---------|-----------|------|-----|----------|--------|

#### 3. Results and Analysis

Through the prediction of the Bayesian artificial neural network system, the data of the total water demand and water supply are predicted. The data of the most important influence factors such as the population, the planting area and the total industrial population are predicted and obtained as well.

High

0.21

0.27

0.38

The figures bellow show the prediction results of these index of the three aspects. It is proved in the undeniable links with the total industrial population, with the increasing of the industrial population, water demand increases in the same tendency. When the development of industry reaches its saturation state, The supply and demand of water resources reach the approximately same level.



Fig.2 The results of the Bayesian artificial network system

### 4. Conclusion

In this study, we establish Bayesian Artificial neural network system. Which uses the tree propagation algorithm in the Bayesian to make the prediction error of Artificial neural network smaller relying on the probabilistic inference.

Using the Bayesian Artificial neural network system to predict the different consequences with or without intervention plan. And when will this scarcity will become a critical issue in the future .

### Acknowledgment

This research has been supported by "A study about the pollution of the air particles in several typical sites "(20142086), which belongs to the innovation and Entrepreneurship Program for College Students in North China electric power university.

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