Risk analysis of rich–poor rainfall encounter in inter-basin water transfer projects based on Bayesian networks

Kang Ling and He Xiaocong

ABSTRACT

An inter-basin water transfer project is one of the effective ways to resolve the problem of an uneven distribution of water resources. Temporal and spatial variations in rainfall in different basins greatly affect water supply and demand in inter-basin water transfer projects, leading to risks to the operation of the water transfer projects. This paper applies a Bayesian network model to analyze this risk and studies the rich–poor rainfall encounter risk between a water source area and water receiving areas in the middle route of the South-to-North Water Transfer Project in China. Real time scenario simulations with the input of new observations were also studied. The results show that the rich–poor rainfall encounter risk is high for the Tangbai River receiving area in the fourth quarter, for the Huai River and South of Hai River receiving area in the second quarter, and for the North of the Hai River receiving area in the fourth and first quarters. The scenario simulations reflect risk change in the operation of water transfer projects, providing scientific decision support for the management of the water resource distribution in the inter-basin water transfer projects.

Key words | Bayesian network, inter-basin water transfer, rich–poor rainfall encounter, risk analysis, South-to-North Water Transfer Project

Kang Ling (corresponding author)
He Xiaocong
Department of Hydropower and Information Engineering,
Huazhong University of Science and Technology,
Wuhan 430074,
China
E-mail: *kling_hust@163.com*

INTRODUCTION

Inter-basin water transfer projects are large-scale hydraulic projects designed to reasonably distribute water resources, improve the population's living environment and boost economic development. There are many long-distance inter-basin water transfer projects around the world, such as the West to East Water Transfer Project in Pakistan (Sarwar *et al.* 2001), the Lesotho Highlands Water Project in Lesotho and South Africa, the National River-Linking Project in India (Jain *et al.* 2005), and Snowy Mountains Scheme in Australia (Pinto *et al.* 2009). To address the water shortage in the north of China, that country has been developing the middle route of the South-to-North Water Transfer Project, which crosses four river basins in China, namely the Yangtze River, Huang River (Yellow River), Huai River and Hai River basins.

An inter-basin water transfer project is an effective way to address an uneven distribution of water resources, although it is accompanied by many risks. Bharati *et al.* (2009) analyzed the risk and consequence of a water transfer project for animals and plants living in the Missouri River and Red River basins. Matete & Hassan (2005, 2006) studied the ecological effects of the Lesotho Highlands Water Project. Gupta & van der Zaag (2008) researched economic, social and environmental risks of an inter-basin water transfer project.

However, the rich–poor rainfall encounter risk resulting from temporal and spatial variations in rainfall in different basins is one of the main risks faced by inter-basin water transfer projects (Zhu *et al.* 2008). If the water source area experiences rich rainfall, the water resource is abundant and the operation of a water transfer project will involve low risk. However, when the water source area and water receiving areas experience poor rainfall at the same time, the operation of a water transfer project faces high risks because of the imbalance of water supply and demand, and actions should be taken to mitigate the risk loss. It is therefore essential to quantify the risk resulting from a

doi: 10.2166/ws.2011.067

rich–poor rainfall encounter between the water source area and water receiving area in water transfer projects.

Commonly used risk analysis methods involve direct integration, Monte-Carlo simulation, analytic hierarchy processing, fuzzy comprehensive evaluation, the maximum entropy principle and Bayesian networks (Sonnemann *et al.* 2003). All other methods calculate risk only from prior probability, while a Bayesian network is a risk analysis method based on Bayesian conditional probability. It not only calculates risk from prior information, but also realizes network reasoning using posterior information, and presents risk changes visually and intelligently (Trucco *et al.* 2008). There is therefore an advantage in using a Bayesian network to analyze the rich–poor rainfall encounter risk in inter-basin water transfer projects.

This paper develops a risk analysis model based on a Bayesian network to analyze the rich–poor rainfall encounter risks of the middle route of the South-to-North Water Transfer Project in China. The paper first explains the necessity of analyzing this kind of risk. A Bayesian network risk analysis model is then employed to assess the rich–poor rainfall encounter risk in the middle route of the South-to-North Water Transfer Project. In the last section, concluding remarks are given.

BAYESIAN NETWORKS

The Bayesian network approach presented here is a comprehensive method based on Bayes probability theorem and graph theory (Baldi & Rosen-Zvi 2005; Castelletti & Soncini-Sessa 2007). It is a directed acyclic graph with network structure. Nodes represent risk factors in risk analysis (Funahashi 1998). The probability relationship between risk factors is represented by a directed edge from one node to another. The uncertainty of risk factors is expressed by prior probability. The quantitative relationship among risk factors is expressed by Bayesian conditional probability and contained in the network as parameters (Lampinen & Vehtari 2001; Sahin *et al.* 2006). The Bayesian network can then reason on the basis of the Bayesian theorem and total probability formula.

The Bayesian theorem states that provided both terms of the ratio exist and $P(A) > 0$, the probability of B conditional on A is

$$P(B|A) = \frac{P(A \cap B)}{P(A)} \tag{1}$$

and total probability formula is

$$P(B) = \sum_{i=1}^{n} P(B|A_i)P(A_i) \quad (i = 1, 2, \ldots, n). \tag{2}$$

Figure 1 illustrates the risk analysis structure of the Bayesian network in analyzing rich–poor rainfall encounter risks in inter-basin water transfer projects, with the parameters required for network reasoning listed next to the nodes.

$P(a_{t+1,j})$ and $P(b_{t+1,n})$ are calculated by the network automatically as:

$$P(a_{t+1,j}) = \sum_{i=1}^{N_i} P(a_{t+1,j}|a_{t,i})P(a_{t,i}), \tag{3}$$

$$P(b_{t+1,n}) = \sum_{m=1}^{N_m} P(b_{t+1,n}|b_{t,m})P(b_{t,m}). \tag{4}$$

The results of risk evaluation are the probability of RISK(t) and RISK($t+1$):

$$P(c_{t,k}) = \sum_{i=1}^{N_i}\sum_{m=1}^{N_m} P(c_{t,k}|a_{t,i}, b_{t,m})P(a_{t,i})P(b_{t,m}), \tag{5}$$

$$P(c_{t+1,k}) = \sum_{j=1}^{N_j}\sum_{n=1}^{N_n} P(c_{t+1,k}|a_{t+1,j}, b_{t+1,n})P(a_{t+1,j})P(b_{t+1,n}). \tag{6}$$

By building a Bayesian network and integrating with its reasoning function, it is an easy task to reason from

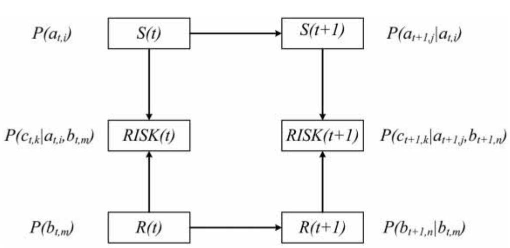

Figure 1 | Bayesian network for analyzing rich–poor rainfall encounter risks in water transfer projects. Here *S* is the water source area and *R* is the water receiving area, RISK is a risk evaluation node, *t* and *t* + 1 denote two adjacent periods, and *i*, *j*, *k*, *m* and *n* denote the discrete states for each node.

incomplete and uncertain knowledge or information, to express and analyze uncertain events and probabilistic events. Moreover, a Bayesian network can intelligently and automatically evaluate risks, display the results in real time and change schematically, making it one of the most effective tools to express and reason uncertain information (Hohenner *et al.* 2005), and thereby raising the prospect of a promising application in risk analysis and decision support.

APPLICATIONS

In this section, a Bayesian network model is built to analyze the rich–poor rainfall encounter risks in the middle route of the South-to-North Water Transfer Project in each quarter of the year. A simulation study was conducted for proposed project operation scenarios, providing scientific decision support for the operation and risk management of the inter-basin water transfer project.

Study areas and data

In China, water resources are rich in the south but poor in the north (Cai 2008). To alleviate water shortage problems in the north, China has been developing the middle route of the South-to-North Water Transfer Project, which will deliver on average 9.5×10^9 cubic metres of water to receiving areas every year after its completion (Wang & Ma 1999). The water transfer line runs 1,432 kilometres, passing four river basins, namely the Yangtze River, the Huang River, the Huai River and the Hai River Basins. The water source area is upstream of the Danjiangkou reservoir, and there are four water receiving areas, namely the Tangbai River water receiving area, the Huai River water receiving area, the South of Hai River water receiving area and the North of Hai River water receiving area (Figure 2). The project will alleviate water shortages in about 20 medium and large cities along the water transfer line, while paying close attention to the ecological environment and agricultural water needs along the water transfer line (Liu & Zheng 2002; Pretner 2007).

The Danjiangkou reservoir is able to seasonally adjust water resources to a certain extent. According to the needs of the water transfer operation of the middle route of the South-to-North water transfer project, this paper takes a quarter as the time scale to analyze the rich–poor encounter risk. Rainfall data for each quarter in the above five regions from 1961 to 2005 were taken for analysis (the hydrological year is from October to the following September, specified according to the water transfer period of this project). Criteria to classify the rainfall state as being rich, normal and poor are listed in Table 1. $x_{62.5\%}$ and $x_{37.5\%}$ are calculated from the rainfall time series employing the experience statistics method, taking a Pearson curve as the theoretical frequency curve for the fitting calculation.

Figure 2 | The middle route of the South-to-North Water Transfer Project in China.

Establishing the Bayesian network

In the rich–poor rainfall encounter risk analysis between water source area and water receiving areas of the middle route of the South-to-North Water Transfer Project, a Bayesian network structure can be defined as in Figure 3.

Table 1 | Standards for classifying the rainfall condition

State	Rich	Normal	Poor
Rainfall	$x \geq x_{62.5\%}$	$x_{37.5\%} < x < x_{62.5\%}$	$x \leq x_{37.5\%}$

In Figure 3, the node 'Danjiangkou (year)' in the first line is the rainfall state of the Danjiangkou water source area in the hydrological year. The nodes in the second line are the rainfall states of the Danjiangkou water source area in each quarter. They are used to determine occurrence probabilities for each rainfall state in each quarter in the water source area. As the hydrological year is from October to September of the following year, risk analysis is conducted in sequence from the fourth quarter to the first, second and third quarters. The quarter node is connected with the year node and the previous quarter node, indicating that the probability distribution of rainfall states for each quarter is determined by the transfer relationship of rainfall states for the hydrological year and the previous quarter. Nodes in the last line are rainfall state nodes during the hydrological year for the four water receiving areas, and nodes in the fourth line are rainfall state nodes in each quarter for water receiving areas, which are used to determine the occurrence probability of rainfall states in each quarter in water receiving areas. The nodes in the third line are risk evaluation nodes for rich–poor rainfall encounter between the water source area and water receiving areas in each quarter, and they are connected with the rainfall states of the water source area and water receiving area in corresponding quarters. Rich–poor rainfall encounter risks are calculated from the rich–poor rainfall states encounters between water source area and water receiving areas in the same quarter.

The Bayesian network shown in Figure 3 has two kinds of parameters: one is the prior probability of root nodes and the other is the conditional probability of state combinations of non-root nodes and their parent nodes.

Parameter identification for network nodes in the water source area and water receiving areas in the hydrological year and in each quarter can be calculated by using formulas (7)–(9) based on rainfall data.

$$P(a_i) = \frac{N(a_i)}{N} \tag{7}$$

$$P(a_i|b_j) = \frac{N(a_i b_j)}{N(b_j)} \tag{8}$$

$$P(a_i|b_j c_k) = \frac{N(a_i b_j c_k)}{N(b_j c_k)} \tag{9}$$

where a_i and b_i $(i = 1, 2, 3)$ denote rainfall states (rich, normal, poor) in the water source area and water receiving areas, respectively.

$N(a_i)$, $N(a_i b_j)$ and $N(a_i b_j c_k)$ denote the frequency of each rainfall state or rainfall state combination; e.g., $a_i b_j$ denotes

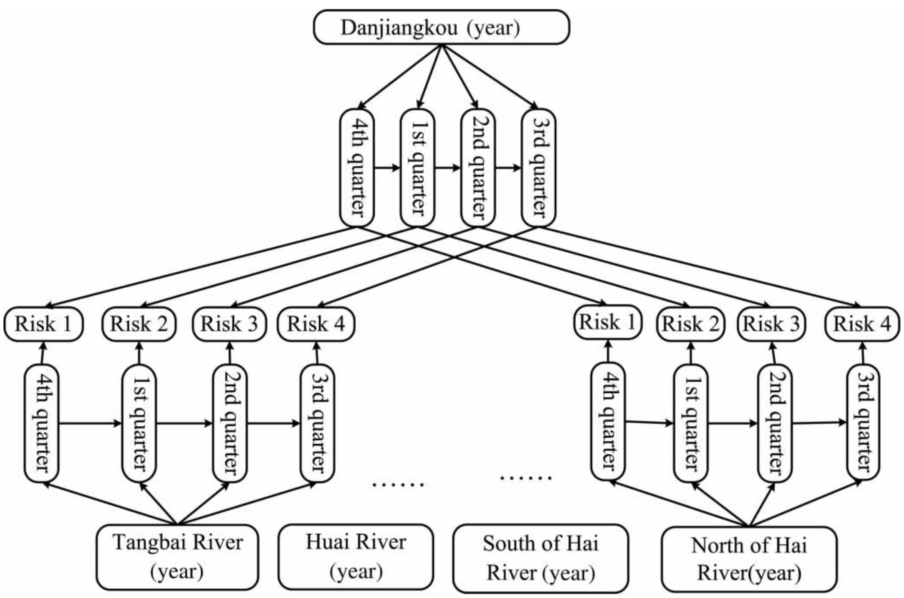

Figure 3 | Bayesian network structure for analyzing the rich–poor rainfall encounter risk in the middle route of the South-to-North Water Transfer Project.

a_i and b_j occurring at the same time. N is the total number of years.

The first quarter for Danjiangkou, for example, has two parent nodes, the Danjiangkou year node and the Danjiangkou fourth quarter node, whose network parameters can be calculated using formulas (7) and (8). According to rainfall data for 45 hydrological years, there were four years when Danjiangkou had a rich rainfall year and rainfall in the fourth quarter was rich too. In those four years, the rainfall level in the first quarter in Danjiangkou was rich in one year, normal in one year, and poor in two years. Thus, $N(b_1c_1) = 4$, $N(a_1b_1c_1) = 1$, $N(a_2b_1c_1) = 1$, $N(a_3b_1c_1) = 1$, and from formula (9), $P(a_1|b_1c_1) = 1/4 = 0.25$. In a similar way, we get $P(a_2|b_1c_1) = 1/4 = 0.25$ and $P(a_3|b_1c_1) = 2/4 = 0.5$ (where a_1 denotes that the rainfall in the first quarter is rich, a_2 denotes that the rainfall in the first quarter is normal, a_3 denotes that the rainfall in the first quarter is poor, b_1 denotes that the hydrological year is wet, $c_1$denotes that the rainfall in the fourth quarter is rich).

The parameters for the Danjiangkou (first quarter) node are given in Table 2.

The parameters of risk evaluation nodes can be determined by expert knowledge. Table 3 presents parameters of risk evaluation nodes defined according to expert knowledge and risk evaluation criteria for the operation of the middle route of the South-to-North Water Transfer Project.

The Bayesian network was built once all network parameters had been defined. Here the Danjiangkou water source area and one of the four water receiving areas, the South of Hai River water receiving area, are used to illustrate

Table 2 | Parameters for Danjiangkou (first quarter) in the Bayesian network

		1st quarter		
Danjiangkou (year)	**4th quarter**	**Rich**	**Normal**	**Dry**
Wet year	Rich	0.25	0.25	0.5
Wet year	Normal	0.167	0.5	0.333
Wet year	Poor	0.25	0.25	0.5
Normal year	Rich	0.333	0.333	0.334
Normal year	Normal	0.333	0.667	0
Normal year	Poor	0.5	0	0.5
Dry year	Rich	0.4	0.4	0.2
Dry year	Normal	0.5	0.25	0.25
Dry year	Poor	0.4	0.2	0.4

Table 3 | Risk evaluation criteria for rich–poor rainfall encounter

		Risk		
Water source area	**Water receiving area**	**High**	**Normal**	**Low**
Rich	Rich	0	0	1
Rich	Normal	0	0	1
Rich	Poor	0	0	1
Normal	Rich	0	1	0
Normal	Normal	0	1	0
Normal	Poor	1	0	0
Poor	Rich	0	1	0
Poor	Normal	1	0	0
Poor	Poor	1	0	0

the application of the Bayesian network model (Figure 4). Bayesian network models were built for the other three water receiving areas in the same way. In Figure 4, S denotes the Danjiangkou water source area and R3 denotes the South of Hai River water receiving area.

Figure 4 shows the occurrence probability of different states for each node. Taking the S (year) node in the first line as an example, in the water source area, the probability of a wet year is 40%, that of a normal year is 20% and that of a dry year is 40%. Analysis of rainfall data recorded over 45 years shows that in the water source area, there were 18 wet years, 9 normal years, and 18 dry years (with the rainfall data for the Danjiangkou water source area in each hydrological year presented in Figure 5, where $x_{37.5\%} = 753$ mm, and $x_{62.5\%} = 849$ mm), giving occurrence probabilities of 40, 20 and 40%, respectively, in good agreement with the Bayesian network reasoning results.

According to the Bayesian network reasoning results, for the Risk 3 node in Figure 4, the rich–poor rainfall encounter risk for the South of Hai river receiving area was high in the second quarter (with high risk probability as high as 42%), indicating that in the second quarter combination of rainfall states for the water source area and the South of Hai river water receiving area had a high probability of being unfavorable. The Risk 2 node shows the rich–poor rainfall encounter risk was normal in the first quarter, and the Risk 1 and 4 nodes show that the occurrence probability of rich–poor rainfall encounter risk was low in the third and fourth quarters.

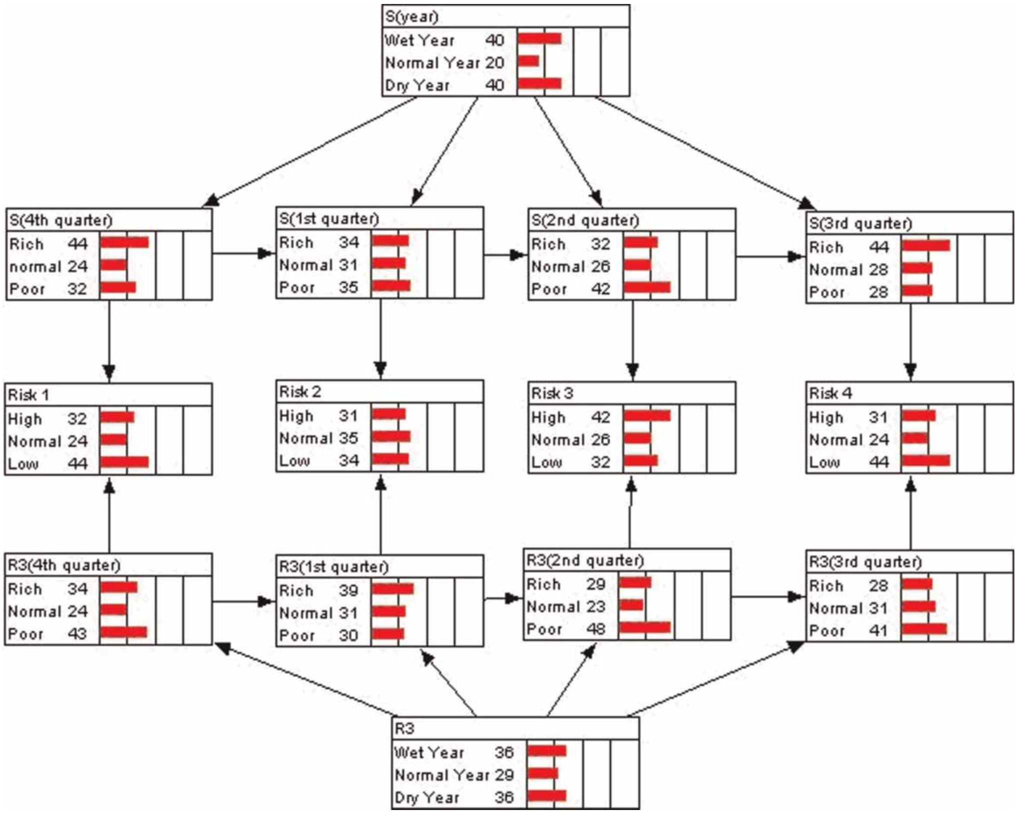

Figure 4 | Bayesian network reasoning based on prior information.

The rich–poor rainfall encounter risks in each quarter for the other three water receiving areas can be calculated in the same way (Table 4).

The evaluation results for the rich–poor rainfall encounter risk between water source area and water receiving areas in Table 4 show that there is a high risk of rich–poor rainfall

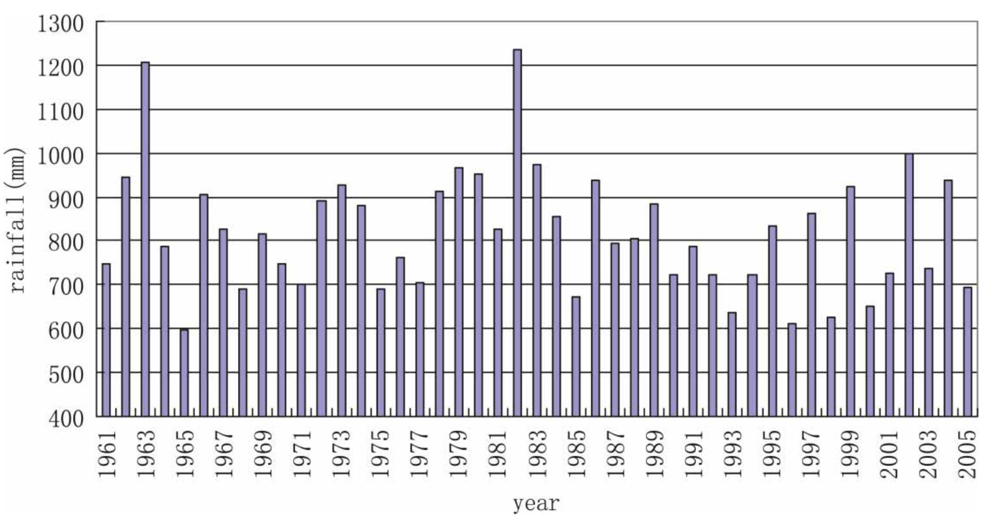

Figure 5 | Rainfall in the Danjiangkou water source area in each hydrological year.

Water Science & Technology: Water Supply | 11.4 | 2011

Table 4 | Rich–poor rainfall encounter risks (%) in each quarter determined by Bayesian networks (H, N and L denote high, normal and low risks, respectively).

	Risk 1			Risk 2			Risk 3			Risk 4		
Water receiving areas	**H**	**N**	**L**	**H**	**N**	**L**	**H**	**N**	**L**	**H**	**N**	**L**
Tangbai River	43	31	26	32	35	33	27	35	38	31	33	36
Huai River	32	32	35	24	36	40	47	28	25	27	31	42
South of Hai River	32	24	44	31	35	34	43	26	32	31	24	44
North of Hai River	41	28	31	42	28	30	35	38	27	31	35	34

encounter for the Tangbai River receiving area in the fourth quarter, for the Huai River and the South of Hai River receiving areas in the second quarter, and for the North of Hai River receiving area in the fourth and first quarter.

The water receiving areas can formulate their water plans and the water transfer project operation department can adjust the water supply order of the four receiving areas to offset water shortage in those areas according to the risk evaluation results. For example, the water transfer project can give water supply priority to the Tangbai River and North of Hai River receiving areas in the fourth quarter because they are at high risk in that period.

Scenario simulations

Risk analysis of rich–poor rainfall encounter between water source area and water receiving area in water transfer projects using a Bayesian network can estimate risk on

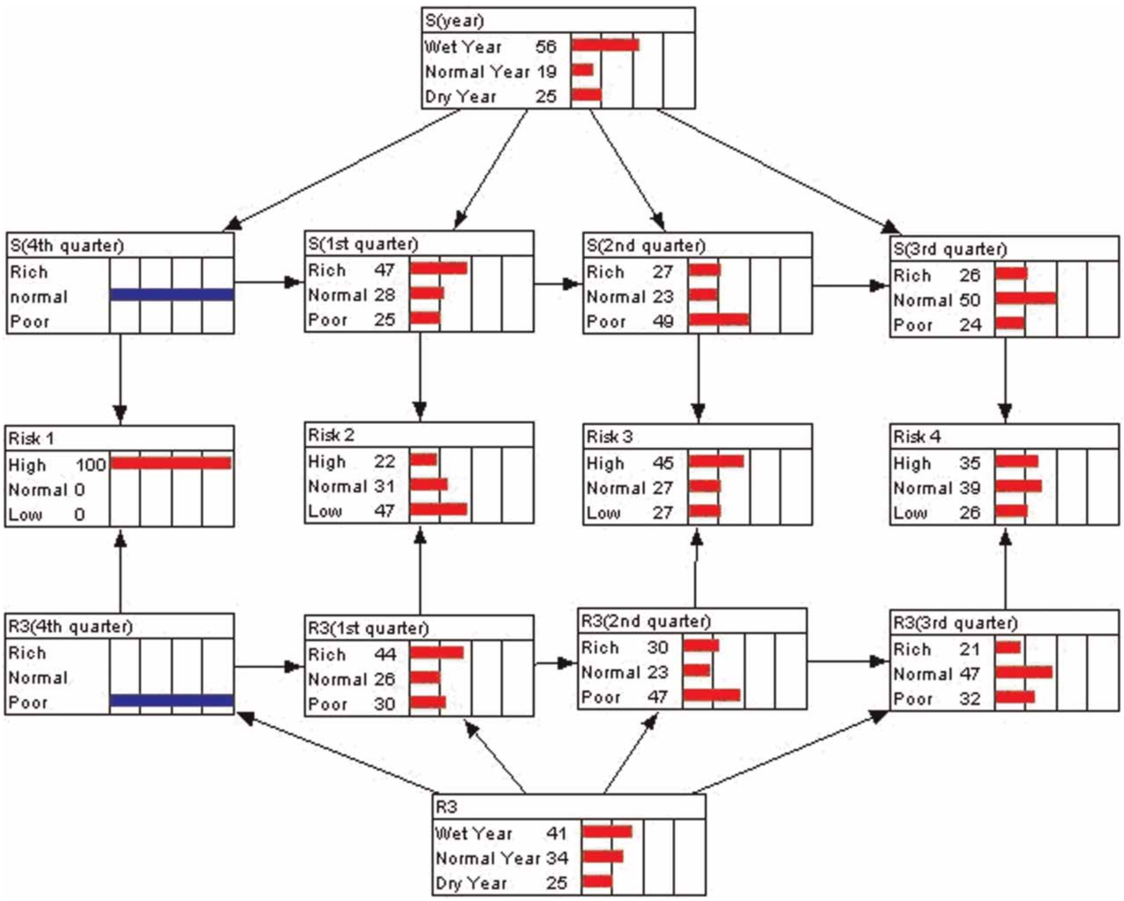

Figure 6 | Network reasoning based on posterior information.

the basis not only of prior information that is added to the network as parameters, but also posterior information, such as observations and simulated scenarios. It is thus possible for engineering managers to control risk changes by adding new information for a real-time evaluation risk.

Let us suppose that, in the fourth quarter, the observed rainfall in the Danjiangkou water source area is normal, while it is poor in the South of Hai River water receiving area. Inputting those observations into the Bayesian network, the states of relevant nodes in the Bayesian network risk analysis model change automatically, as shown in Figure 6.

After importing new observations of rainfall states in the fourth quarter, the Bayesian network again evaluates the risk of water transfer. Comparing risk nodes in Figure 4 with those in Figure 6, we see that the rich–poor encounter risks for each quarter change. For the first quarter, the low risk probability increases from 34 to 47%. For the second quarter, the high risk probability increases from 42 to 45%. For the third quarter, the low risk probability decreases from 44 to 26%.

The occurrence probabilities of different rainfall states for the whole hydrological year also change. The probability of a wet year for the water source area increases from 40 to 56%, while the probability of a wet year for the South of Hai river water receiving area increases from 36 to 41%. The results calculated using the Bayesian network model show that when the rainfall was normal in the water source area and poor in the South of Hai river water receiving area in the fourth quarter, there was a probability as high as 56% for a wet year in the water source area, and a probability of up to 41% for a wet year in the South of Hai river water receiving area.

CONCLUSIONS

In the current study, a Bayesian network risk model was built for rich–poor rainfall encounter risks resulting from temporal and spatial variations in rainfall in water source areas and water receiving areas in inter-basin water transfer projects. Taking the middle route of the South-to-North water transfer project in China as an example, the risks of rich–poor rainfall encounter between water source area and water receiving areas in each quarter in four water receiving areas were analyzed. Scenario simulations were also carried out with the input of new observations. The calculation results show that the rich–poor rainfall encounter risk is high for the Tangbai River receiving area in the fourth quarter, for the Huai River and the South of Hai River receiving areas in the second quarter, and for the North of Hai River receiving area in the fourth and first quarters. The scenario simulations reflect risk change according to newly observed information, which will benefit risk management in the operation of water transfer projects. Analysis of rich–poor rainfall encounter risk based on Bayesian networks can provide scientific decision support for the distribution of water resources in inter-basin water transfer projects.

ACKNOWLEDGEMENT

The authors appreciate support provided by the Key Project of the National Eleventh Five-Year Research Program of China (2006BAB04A09).

REFERENCES

Baldi, P. & Rosen-Zvi, M. 2005 On the relationship between deterministic and probabilistic directed Graphical models: from Bayesian networks to recursive neural networks. *Neural Networks* **18** (8), 1080–1086.

Bharati, L., Smakhtin, V. U. & Anand, B. K. 2009 Modeling water supply and demand scenarios: the Godavari–Krishna inter-basin transfer India. *Water Policy* **11**, 140–153.

Cai, X. 2008 Water stress, water transfer and social equity in Northern China – implications for policy reforms. *Journal of Environmental Management* **87** (1), 14–25.

Castelletti, A. & Soncini-Sessa, R. 2007 Bayesian networks and participatory modelling in water resource management. *Environmental Modelling & Software* **22** (8), 1075–1088.

Funahashi, K. 1998 Multilayer neural networks and Bayes decision theory. *Neural Networks* **11** (2), 209–213.

Gupta, J. & van der Zaag, P. 2008 Interbrain water transfers and integrated water resources management: where engineering, science and politics interlock. *Physics and Chemistry of the Earth, A/B/C* **33** (4), 28–40.

Hohenner, M., Wachsmuth, S. & Sagerer, G. 2005 Modeling expertise for structure elucidation in organic chemistry using Bayesian networks. *Knowledge-Based Systems* **18** (4–5), 207–215.

Jain, S. K., Reddy, N. & Chaube, U. C. 2005 Analysis of a large inter-basin water transfer system in India. *Hydrological Sciences Journal* **50** (1), 125–137.

Lampinen, J. & Vehtari, A. 2001 Bayesian approach for neural networks – review and case studies. *Neural Networks* **14** (3), 257–274.

Liu, C. & Zheng, H. 2002 South-to-north water transfer schemes for China. *International Journal of Water Resources Development* **18** (3), 453–471.

Matete, M. & Hassan, R. 2005 An ecological economics framework for assessing environmental flows: the case of inter-basin water transfers in Lesotho. *Global and Planetary Change* **47** (3), 193–200.

Matete, M. & Hassan, R. 2006 Integrated ecological economics accounting approach to evaluation of inter-basin water transfers: an application to the Lesotho Highlands Water Project. *Ecological Economics* **60** (5), 246–259.

Pinto, P. C., Nagele, A., Dejori, M., Runkler, T. A. & Sousa, J. M. C. 2009 Using a local discovery ant algorithm for Bayesian network structure learning. *IEEE Transactions on Evolutionary Computation* **13** (4), 767–779.

Pretner, A. 2007 *Introduction to the International Water Transfer Projects and Comparison with the East Route of Chinese South to North Water Transfer Project*. In 3rd International Yellow River Forum, Dongying City, China, pp. 55–66.

Sahin, S. Ö., Ülengin, F. & Ülengin, B. 2006 A Bayesian causal map for inflation analysis: the case of Turkey. *European Journal of Operational Research* **175** (2), 1268–1284.

Sarwar, A., Bastiaanssen, W. G. M. & Feddes, R. A. 2001 Irrigation water distribution and long-term effects on crop and environment. *Agricultural Water Management* **50** (6), 125–140.

Sonnemann, G. W., Schuhmacher, M. & Castells, F. 2003 Uncertainty assessment by a Monte Carlo simulation in a life cycle inventory of electricity produced by a waste incinerator. *Journal of Cleaner Production* **11** (3), 279–292.

Trucco, P., Cagno, E., Ruggeri, F. & Grande, O. 2008 A Bayesian Belief Network modelling of organisational factors in risk analysis: a case study in maritime transportation. *Reliability Engineering & System Safety* **93** (6), 845–856.

Wang, L. & Ma, C. 1999 A study on the environmental geology of the Middle Route Project of the South–North water transfer. *Engineering Geology* **51** (3), 153–165.

Zhu, Y. P., Zhang, H. P., Chen, L. & Zhao, J. F. 2008 Influence of the South–North Water Diversion Project and the mitigation projects on the water quality of Han River. *Science of the Total Environment* **406** (2), 57–68.

First received 26 January 2011; accepted in revised form 20 June 2011