Desalination and Water Treatment
www.deswater.com

doi: 10.1080/19443994.2015.1110047

57 (2016) 20774–20783
September

Taylor & Francis
Taylor & Francis Group

A new fault diagnosis method based on Bayesian network model in a wastewater treatment plant of northern China

Liang Guo[a,b], Ying Zhao[a,b,*], Fu-yi Cui[a,b,*]

[a]*School of Municipal and Environmental Engineering, Harbin Institute of Technology, Harbin 150090, China, Tel. +86 045186283109; emails: guoliang0617@hit.eud.cn (L. Guo), zhaoying@hit.edu.cn (Y. Zhao), Tel. +86 045186282098; email: cuifuyi@hit.edu.cn (F.-Y. Cui)*
[b]*State Key Laboratory of Urban Water Resource and Environment, Harbin Institute of Technology, Harbin 150090, China*

Received 14 January 2015; Accepted 14 October 2015

ABSTRACT

A novel diagnosing faults method is presented using a Bayesian network (BNT) model to optimize system diagnosis for a wastewater treatment plant (WTP) in northern China. The BNT model is established according to the expert knowledge based on local conditions. The historical data of the WTP are employed to implement the parameter learning of the BNT model. Some practical cases are carried out by the BNT model based on the Bayesian inference. The diagnostic results are compared with the monitoring data of that day to verify accuracy of the BNT model. Meanwhile, several fault diagnosis results and improvement measures are given in this study. The results show that the proposed method is robust enough to diagnose the faults quickly and accurately so as to optimize the operation of the WTP.

Keywords: Bayesian network model; Fault diagnosis; Wastewater treatment plant; A^2/O process; Bayesian inference

1. Introduction

With the rapid development of industrial and population growth and urbanization of China in the last decades, the wastewater is greatly increasing, resulting in high frequency of river pollutions and tremendous pressure for wastewater treatment plant (WTP) [1]. The effective wastewater treatment becomes a key factor to ensure the security of water environment [2]. Therefore, all the treatment processes of WTP should be properly operated and the faults should be reduced to improve purifying capacity.

The water quality of raw wastewater always changes with the time, so that the processes parameters of WTP should be adjusted according to the changes. Otherwise, the process parameters will be unmatched resulting in the purifying capacity dropping and fault appearing. Meanwhile, the equipment failures and human errors usually happen in the complex systems in WTP, including many processes and according to multitudinous parameters. Such faults can lead to unqualified effluent water quality of WTP. The quick fault diagnosis of WTP is necessary as it is capable of finding out the source of fault and keeping the purifying capacity stable. The fault diagnosis technology is a way to find out the source and reason for the fault through some key visible and measurable indexes, and several solutions can be given by the technology [3]. Several methods, including Artificial Neural Network (ANN) [4,5], Support Vector Machine (SVM) [6,7], and

*Corresponding authors.

Rough Sets Theory (RS) [8,9] are used in fault diagnosis by scholars from different countries. These fault diagnosis methods have been applied previously in power systems.

In recent years, Bayesian method has been increasingly applied to study uncertainty in many fields. The prominent advantage of Bayesian statistics is their capability of transforming the uncertainty problem into estimated model parameters in terms of a joint posterior distribution [10–15]. Bayesian networks (BNT) based on Bayesian statistics have been applied increasingly to study fault diagnosis using more intuitive graphics and an exact probabilistic inference method, which is excellent to point out the complex and uncertainty problem [16–18]. In order to increase the diagnostic accuracy of ground-source heat pump (GSHP) system, especially for multiple-simultaneous faults, Yonghong Liu proposed a multi-source information fusion-based fault diagnosis methodology using BNT. BNTs are considered as one of the most useful models in the field of probabilistic knowledge representation and reasoning, as the capability of dealing with the uncertainty problem of fault diagnosis. The cases show that the multi-source information fusion-based fault diagnosis model using Bayesian network is effectual for GSHP system [19]. A Bayesian network is used to address the fault diagnosis of motor bearing. The results also show the proposed Bayesian model can diagnose faults effectively [20]. Ferat Sahin has successfully implemented a fault diagnosis technique for airplane engines using the particle swarm optimization (PSO) algorithm for learning the structure of a BN from a large data-set. The results show that a Bayesian network can be learned from engine data and successful inference can be performed to detect the anomalies or faults in the sensor readings of an airplane engine [21]. The studies indicate that the BNT is a robust tool for fault diagnosis, which can significantly increase the diagnostic accuracy. However, the BNTs are seldom used in the fault diagnosis of WTP systems.

In this paper, a BNT model is employed to address the fault diagnosis of a WTP in northern China. All parameters of the WTP are analyzed by the expert knowledge based on local conditions, including the raw water quality, effluent water quality, and the controlled parameters. Some key parameters are used as nodes to set up the BNT model. The historical data of the WTP are used to implement the parameter learning of the BNT. Some practical cases are carried out by the BNT model based on the Bayesian inference. Meanwhile, several fault diagnosis results and improvement measures are given in this study. The BNTs is supposed to be a useful tool for improving purifying ability of wastewater and finding out the faults quickly and accurately so as to optimize the operation of the WTP.

2. Materials and Methods

2.1. Study WTP and data source

The multiple-influent improved A^2/O process is applied in this study instead of the traditional process, which can denitrify the nitrates in returned activated sludge by the addition of pre-anoxic zone in front of an anaerobic tank. Meanwhile, the improved process can reduce the impact of nitrates on phosphorus release in the anaerobic zone and ensure the stable operation of anaerobic phrase [22]. In addition, the multiple-influent wastewater flows down the pre-anoxic and anoxic zones according to a certain proportion which can solve the problem of poor carbon source for denitrification to improve the nitrogen removal efficiency. The diagram of the detailed process is shown in Fig. 1.

First, the denitrification of the returned activated sludge is completed in the pre-anoxic zone which can reduce the competition between denitrifying bacteria and PAOS for carbon sources. Wastewater together with the returned sludge from clarifier flowed into the anaerobic phrase, completed the ammoniation reaction and removed a part of BOD_5. The major function of anoxic zone is to accomplish the nitrate–nitrogen denitrification flowing from the aerobic zone by the inner loop. The ammoniation of organic nitrogen and nitrification of NH3–N can be completed in the aeration zone with further removal of BOD_5 and COD. The wastewater is then separated into sludge and water in a secondary clarifier and a proportion of sludge is pumped into the pre-anoxic zone with a small part discharged as excess sludge. Finally, the supernate is discharged as treated water.

The data of water quality and process parameters are considered in this study including raw water quality, effluent water quality, and key control parameters of the process. Daily, data are collected for two years in a WTP of northern China. The data are used to train the BNT model. Considering the local conditions and wastewater discharge standard [23], the raw water quality and effluent water quality are designed in Table 1. Some key control parameters of the process are designed in Table 2.

2.2. Bayesian approach

2.2.1. Bayesian network

A Bayesian network is a probabilistic graphical model (a type of statistical model) that represents a

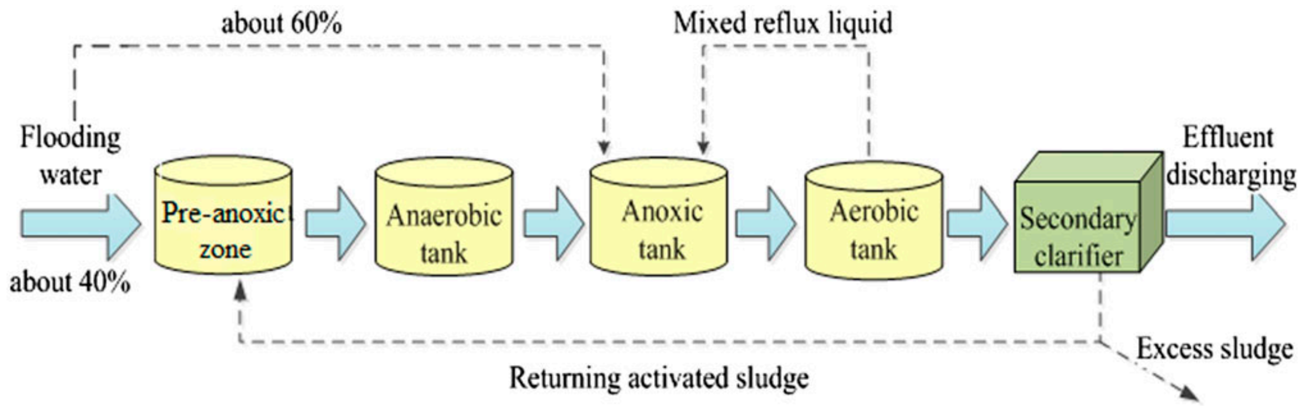

Fig. 1. Improved A^2/O process of a WTP in north China.

Table 1
Design of raw water quality and effluent water quality of the WTP

Parameter	pH	COD_{cr} (mg/L)	BOD_5 (mg/L)	SS (mg/L)	NH_3-N (mg/L)	TN (mg/L)	TP (mg/L)
Raw water quality	6.5–9.0	500	220	250	40	50	5.0
Effluent water quality	6.0–9.0	60	20	20	8(15[a])	20	1.0

[a]It is the control value when water temperature is under 12˚.

Table 2
Some key control parameters of the A^2/O process of the WTP

Parameters of the process	Values
Mixed liquor suspended solids (MLSS)/(mg/L)	3,000–4,000
TN loading (L_{TN})/kg TN/(kg MLSS d)	<0.05
TP loading (L_{TP})/kg TN/(kg MLSS d)	<0.06
Sludge return ratio (R/%)	50–70
Nitrification liquid reflux ratio ($R_{interior}$ /%)	100–150
Dissolved oxygen of aerobic tank (DO)/(mg/L)	2.0–3.5
Hydraulic retention time (HRT)/h	19.5
Oxido-reduction potential of anoxic tank (ORP)/(mv)	≤–100
Sludge loading (F/M ratio)/kg BOD/(kg MLSS·d)	0.1–0.2
Sludge volume index (SVI)	70–150
Carbon nitrogen ratio (COD/TN)	>8
BOD_5/TP	>17

set of random variables and their conditional dependencies via a directed acyclic graph (DAG). For example, a Bayesian network could represent the probabilistic relationships between diseases and symptoms. Given the symptoms, the network can be used to compute the probabilities of the presence of various diseases. Formally, Bayesian networks are DAGs whose nodes represent random variables in the Bayesian sense: they may be observable quantities, latent variables, unknown parameters, or hypotheses. Edges represent conditional dependencies; nodes that are not connected represent variables that are conditionally independent of each other. Each node is associated with a probability function that takes, as input, a particular set of values for the node's parent variables, and gives (as output) the probability (or probability distribution, if applicable) of the variable represented by the node. For example, if m parent nodes represent m Boolean variables then the probability function could be represented by a table of 2^m entries, one entry for each of the 2^m possible combinations of its parents being true or false. Efficient algorithms exist that perform inference and learning in Bayesian networks [24].

2.2.2. Learning and Inference

The learnings include parameter and structure. In order to fully specify the Bayesian network and thus fully represent the joint probability distribution, it is necessary to specify for each node *X* the probability distribution for *X* conditional upon *X*'s parents. The distribution of *X* conditional upon its parents may have any form. Often these conditional distributions include parameters which are unknown and must be estimated from data, often using the maximum likelihood or Bayesian estimation approach [25]. The Bayesian estimation approach is used to perform parameter learning in this study. In the simplest case, a Bayesian network is specified by an expert and is then used to perform inference. In other applications the task of defining the network is too complex for humans [26]. In this case, the network structure and the parameters of the local distributions must be learned from data. In the study, the network structure is specified by known expert because the network is not complex.

Because a Bayesian network is a complete model for the variables and their relationships, it can be used to answer probabilistic queries about them. For example, the network can be used to find out updated knowledge of the state of a subset of variables when other variables (the evidence variables) are observed. This process of computing the posterior distribution of variables given evidence is called probabilistic inference. The posterior gives a universal sufficient statistic for detection applications, when one wants to choose values for the variable subset for minimizing some expected loss function, for instance the probability of decision error. A Bayesian network can thus be considered a mechanism for automatically applying Bayes' theorem to complex problems. The inferences include causal inference (forward inference) and diagnostic inference (reverse inference). The two inferences are used in this study. The forward inference is used to predict and analyze and reverse inference is used to find the cause of fault. Two inference algorithms are usually used, including accurate inference algorithm and approximate inference algorithm [27]. Clique tree propagation algorithm is used in inference in this study, which is accurate inference algorithm. Meanwhile, the software Netica 5.05 is used to perform the inference and analysis.

2.3. The BNT model for fault diagnosis in the WTP

2.3.1. The node of BNT model

Theoretically, although all factors can be taken as the node of BNT model, a complex BNT model is susceptible to bad training and might harm the performance of the network [2]. Many parameters change slightly in all processes and can be treated as a constant. The literature indicates that an appropriate BNT model has good inferential capability [28]. Therefore, some key parameters are selected as the nodes of the BNT model, including raw water quality, effluent water quality, and control parameters. Three kinds of node are shown in Table 3.

The ORP is supposed to reflect the influence on the life and activity of micro-organism by the DO. And the FM can express accurately the change in sludge age (SRT) for they are correlated closely. The FM is used to express the SRT in this study for it can be easily obtained. The sludge return ratio is controlled in a reasonable range and can be adjusted according to practical scenes. Other control parameters always change slightly and are taken as constants.

2.3.2. Definition of node status of BNT model

Discretization is done for all variables, including raw water quality, effluent water quality, and control parameters. The statuses of all variables (nodes) are defined by expert knowledge and practical conditions. The effluent water quality must reach the B standard in the first level of wastewater discharge standard [20]. The status of the variable is defined from the average value or designed value by the Gaussian distribution, including low value, high value, and normal value. The statuses of all variables are shown in Table 4.

2.3.3. Structure of BNT model

Based on the expert knowledge, literature investigation, and operation situation of the WTP, the relationship of all nodes are defined to build the BNT model. The structure of the BNT model is shown in Fig. 2, including upper layer, inter layer, and lower layer. The variables of raw water quality are in the upper layer, the variables of effluent water quality are in the lower layer, and the variables of all control parameters are in the inter layer. The arrows express the relationship of nodes in the BNT model. FM can be affected by COD_in, Q, and MLSS. COD_out and NH_3_out are both affected by FM, T, and DO. Meanwhile, NH_3_in can influence NH_3_out. The CN, T, and ORP are important factors to influence denitrification. Denitrification can be weakened under lacking carbon source. A low water temperature will restrain the movement of denitrifying bacteria resulting in a low biological treatment efficiency. The ORP can be affected by R_interior and DO.

Table 3
Three kinds of variables in the BNT model

Node		Symbol
Type	Name	
Raw water quality	COD	COD_in
	NH_3-N	NH_3_N
	TN	TN_in
	Quantity	Q
Effluent water quality	COD	COD_OUT
	NH_3-N	NH_3_OUT
	TN	TN_OUT
Control paramaters	Water temperature	T
	Sludge loading (FM ratio)	FM_ratio
	Mixed liquor suspended solids (MLSS)	MLSS
	Carbon nitrogen ratio (COD/TN)	CN_ratio
	Nitrigfication Liquid reflux ratio ($R_{interior}$)	R_interior
	Dissolved oxygen of aerobic tank (DO)	DO
	Oxido-reduction potential of anoxic tank (ORP)	ORP

Table 4
Definition of node status of BNT model

Variable		Symbol	Unit	Status		
Type	Name			Low	Normal	High
(a) Raw water quality						
Raw water quality	COD	COD_in	mg/L	<500	500–620	>620
	NH_3_N	NH_3_N	mg/L	<40	40–65	>65
	TN	TN_in	mg/L	<50	50–80	>80
	Quanity	Q	mg/L	<55,000	55000–65000	>65000
(b) Control parameters						
Control parameters	Sludge loading	FM_ratio	kg COD/(kg MLSS d)	<0.1	0.1–0.2	>0.2
	Mixed liquor suspended solids	MLSS	mg/L	<3000	3000–4000	>4000
	Water temperature	T		<10	10–20	>20
	Carbon nitrogen ratio	CN_ratio	–	<8	–	>8
	Nitrification liquid reflux ratio	R_interiro	%	<100	100–150	>150
	Dissolved oxygen of aerobic tank	DO	mg/L	<2.0	2.0–3.5	>3.5
	Oxido-reduction potential of aerobic tank	ORP	mv	<–100	–	>–100
(c) Effluent water quality						
Variable		Symbol	Unit	State		
Type	Name			Normal	–	Abnormal
Effluent water quality	COD	COD_out	mg/L	<60	–	>60
	NH_3_N	NH_3_N	mg/L	<8	–	>8
	TN	TN_out	mg/L	<20	–	>20

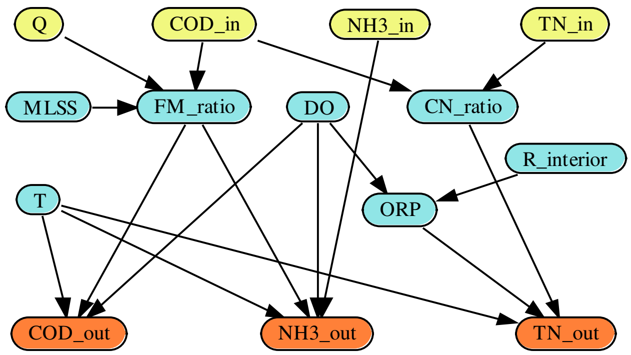

Fig. 2. Model structure of diagnostic BNT.

A high R_interior or DO indicates that excess dissolved oxygen will be taken into the pre-anoxic zone resulting in abnormal ORP.

2.3.4. Parameter of BNT model

Besides the structure of BNT model, the parameter of BNT model is also a key element for modeling. The model is trained by historical data. The training data include 630 groups monitoring data of a WTP in northern China, such as raw water quality, effluent water quality, and control parameters. The software Netica 5.05 and clique tree propagation algorithm are used to train the BNT model. The training results are prior probabilities of all nodes in the Bayesian network. When new failure data of the WTP are considered, posterior probabilities of the nodes will be computed by Bayesian estimation. The faults of the processes can be diagnosed from the posterior probabilities.

2.3.5. Model fitting test and application

A real fault case of the WTP is given to illustrate the application of the proposed BNT model. The diagnostic result with BNT model will be compared with the real cause of the fault, which is obtained from many tests and adjustment of the processes. The correctness of BNT model will be verified. At the same time, solution of the fault will be given to help managers to correct and adjust the processes resulting in improving wastewater purification ability.

3. Results and discussion

3.1. Prior probability of the BNT model

The BNT model is trained with historical data. The more enough data can be considered for training the model, the more accurate results will be obtained. Usually, the enough data should include much historical data and fault information. Therefore, in this study, 630 groups monitoring data of a WTP in northern China are selected as training data, including some fault information. And the training results are prior probabilities of all nodes in the Bayesian network. Marginal probability distribution or joint probability distribution is computed for each node of the BNT model. Especially, the prior probability is marginal probability for the nodes with no father node, including Q, COD_in, NH_3_in, TN_in, MLSS, Do, T, and R_interior. Meanwhile, the prior probability is a joint probability for the nodes with a father node. The prior probabilities of all nodes are shown in Fig. 3.

3.2. The validation and application of the BNT model in the WTP

The developed BNT model is applied in a real fault case of the WTP to demonstrate its validation to diagnose fault in optimized operation of the WTP. The effluent water quality is found abnormal at T_0 (some time) of some day in December of 2013. The real fault case contains three points: (1) COD_out > 60 mg/L, (2) NH_3_out > 8 mg/L, and (3) TN_out is normal. In order to make the reasoning results more precise, the reasoning process is going stepwise. Four steps are designed: (1) *A*: the prior probability with no new information (evidence), (2) *B*: the posterior probability with abnormal NH_3_out, (3) *C*: the posterior probability with abnormal COD_out and NH_3_out, and (4) *D*: the posterior probability with control parameters of processes.

The reasoning process is shown in Table 5. And the probability of nodes in *A* is similar to Fig. 4. Most statuses are normal in the nodes of *A*. The new evidence is inputted, where NH_3_out is abnormal, the posterior probability is estimated by the BNT model. The change can be seen in *B* row:

(1) The probability of abnormal rises from 0.098 to 0.306 for COD_out.
(2) The probability of abnormal rises from 0.128 to 0.347 for TN_out.
(3) The probability of high rises from 0.046 to 0.187 for FM_ratio.
(4) The probability of low rises from 0.057 to 0.270 for DO.
(5) The probability of low rises from 0.087 to 0.186 for T.
(6) The probability of high rises from 0.057 to 0.148 for NH_3_in.

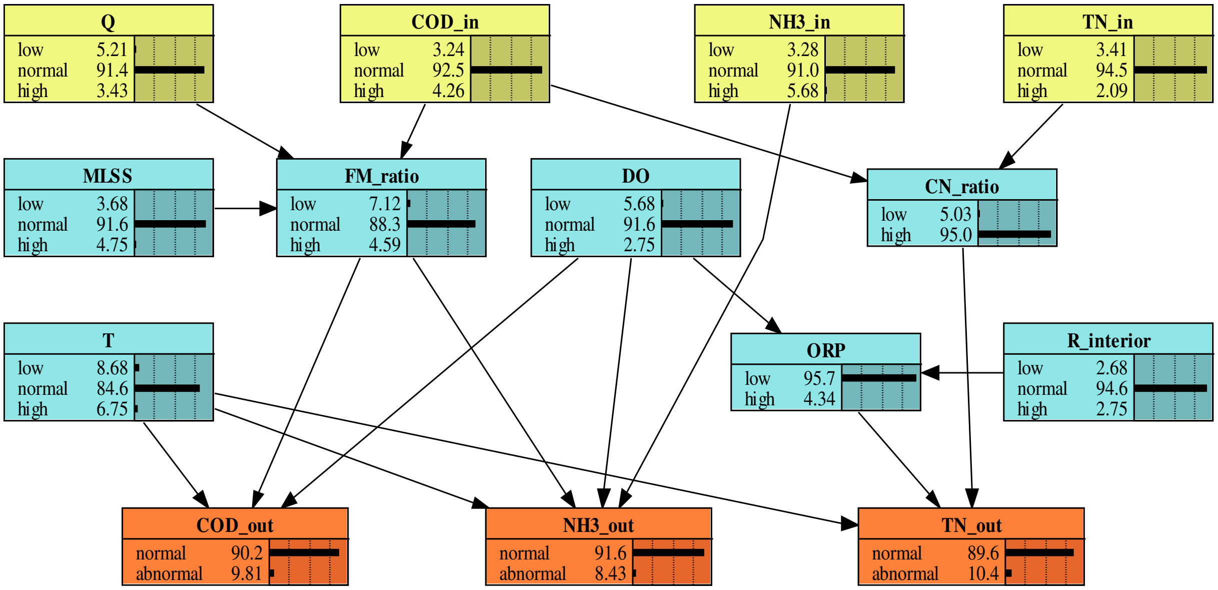

Fig. 3. Prior probability of all nodes in the Bayesian network.

Table 5
Reasoning process of fault diagnosis based on Bayesian network

Node	Status	*A*	*B*	*C*	*D*	Node	Status	*A*	*B*	*C*	*D*
Q	Low	0.052	0.107	0	0	FM_ratio	Low	0.071	0.099	0.043	0.053
	Normal	0.914	0.855	1	1		Normal	0.883	0.714	0.822	0.870
	High	0.034	0.038	0	0		High	0.046	0.187	0.135	0.077
COD_in	Low	0.032	0.037	0	0	DO	Low	0.057	0.270	0.707	0
	Normal	0.925	0.884	1	1		Normal	0.916	0.722	0.288	1
	High	0.043	0.079	0	0		High	0.027	0.008	0.005	0
NH_3_in	Low	0.033	0.048	0	0	MLSS	Low	0.037	0.090	0.042	0
	Normal	0.910	0.804	1	1		Normal	0.916	0.874	0.896	1
	High	0.057	0.148	0	0		High	0.047	0.036	0.062	0
TN_in	Low	0.034	0.033	0	0	T	Low	0.087	0.186	0.343	0.907
	Normal	0.945	0.946	1	1		Normal	0.846	0.754	0.608	0.089
	High	0.021	0.021	0	0		High	0.067	0.060	0.049	0.004
COD_out	Normal	0.902	0.694	0	0	ORP	Low	0.957	0.959	0.970	1
	Abnormal	0.098	0.306	1	1		High	0.043	0.041	0.030	0
NH_3_out	Normal	0.916	0	0	0	CN_ratio	Low	0.050	0.054	0.011	0.011
	Abnormal	0.084	1	1	1		High	0.950	0.946	0.989	0.989
R_interior	low	0.027	0.028	0.027	0	TN_out	Normal	0.896	0.871	1	1
	Normal	0.946	0.945	0.953	1		Abnormal	0.104	0.129	0	0
	High	0.027	0.027	0.020	0						

The main causes are analyzed according to the above change in probability and actual conditions: (1) FM_ratio is high, (2) DO is low, (3) T is low, and (4) NH_3_in is high. One or more causes lead to abnormal NH_3_out. Though the probability of abnormal factor rises for TN_out, it is still in a normal range at T_0 from monitoring record of that day. But the COD_out is abnormal from the record. New evidences are obtained from new monitoring data, including Q, COD_in, NH_3_in, and TN_in. The hydraulic retention time (HRT) is 19.5 h. Because we can find the fault 19.5 h later than the real happened time, the new evidence is the monitoring data 19.5 h before than the time we find the fault. The posterior probability is estimated by new evidences, which can be seen in *C* row of Table 5.

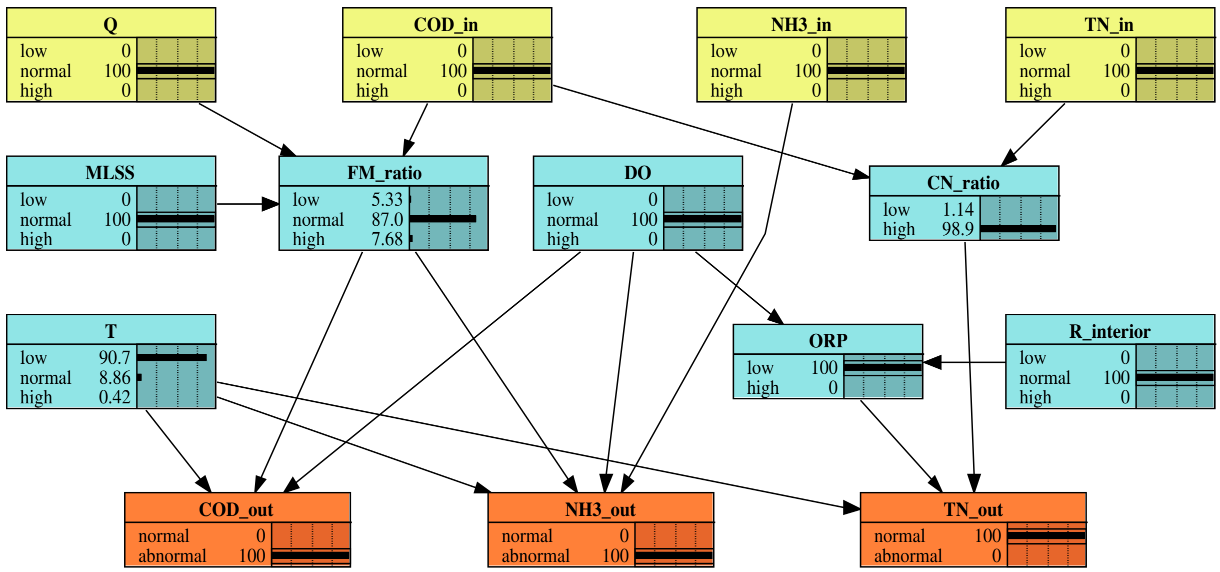

Fig. 4. Posterior probability of all nodes in the BNT model.

The changes are obtained from *B* to *C*:

(1) The probability of normal rises from 0.714 to 0.822 for FM_ratio.
(2) The probability of low rises from 0.270 to 0.707 for DO.
(3) The probability of low rises from 0.186 to 0.343 for T.

The main causes are also analyzed for abnormal COD_out and NH_3_out. There are two causes: (1) DO is low and (2) T is low. Meanwhile, the FM_ratio returns to normal. Some control parameters of processes will be inputted in the BNT model as new evidences. MLSS is 3,186 mg/L (normal). R_interior is 150% (normal). ORP is −179 mv (low). DO is 2.2 mg/L (normal). The diagnostic result is shown in Fig. 4, which is similar to *D* row in Table 5.

The result indicates that FM_ratio further returns to normal. But, the probability of low factor rises from 0.343 to 0.907 for T. Other parameters are all in normal status. So, low temperature is the main cause for abnormal COD_out and NH_3_out. The diagnostic result is compared with the monitoring data of that day. The water temperature of the day is only 7 degree. The movement of micro-organism can be restrained resulting in bad aerobic degradation and nitrification. The purifying capacity of wastewater drops and COD_out and NH_3_out are abnormal. Previously, the real cause of fault was obtained from many tests, so it would require much time and persons to find and usually cost much money. Now the cause can be reasoned quickly and accurately by the BNT model. The diagnostic result is consistent with the real scene. It indicates the BNT model is a robust tool for fault diagnosis in WTPs.

The improvement measures will be given for the diagnostic result in this paper. Return sludge ratio should be increased and sludge emissions should be reduced for keeping quantity of the microorganism high and reducing the FM_ratio. At the same time, aeration should be enhanced for good nitrification. The WTP is located in north China and the local climate has distinct seasonal variation. The difference in average water temperature between summer and winter exceeds 30˚, so raw wastewater and other parameters of the WTP have obvious seasonal characteristics. Therefore, an air heater and an air blower should be used in the aeration tank to enhance air temperature in winter. The sludge is heated properly. And heat preservation should be done for all structures of the WTP for improving removal efficiency of micro-organism under a low temperature condition.

4. Conclusion

In this paper, a BNT model is used to address the fault diagnosis of a WTP in northern China. All variables are analyzed in WTP by expert knowledge based on local condition, the BNT model is established according to some important variables, including raw water quality, effluent water quality, and some key control parameters. The historical data of the WTP are used to implement the parameter learning of the BNT model. Some practical cases would be carried out by the BNT model based on the Bayesian inference. The diagnostic result is compared with the monitoring data of that day. Previously, the real cause of fault was obtained from many tests, so it requires much time and persons to find and maybe cost much money. Comparing with the traditional method, the prominent advantage of BNT model is to reason the fault cause quickly and accurately. The diagnostic result is consistent with the real scene. It indicates the BNT model is a robust tool for fault diagnosis in WTPs.

Despite encouraging results on verification and efficacy, the proposed model can still be improved with more historical data, fault information, and accurate expert knowledge. A more comprehensive study on influencing factors can be done in the future study, the fault diagnosis method will be further improved, accordingly, the results might become even more accurate.

Acknowledgment

This paper is supported by the National Natural Science Fund Project of China (No. 71471050); National Science Foundation for Young Scholars of China (No. 71203041), Research and Innovation Fund project of Harbin Institute of Technology (HIT) in 2011.

Reference

[1] P. Yuan, X. Zhu, The current situation of fresh water and the management strategy in China, Pearl River Modern Constr. 5 (2014) 18–23.

[2] Y. Zhao, L. Guo, J. Liang, M. Zhang, Seasonal artificial neural network model for water quality prediction via a clustering analysis method in a wastewater treatment plant of China, Desalin. Water Treat. (2014), doi:10.1080/19443994.2014.986202.

[3] S. Verron, T. Tiplica, A. Kobi, Fault diagnosis of industrial systems by conditional Gaussian network including a distance rejection criterion, Eng. Appl. Artif. Intell. 23 (7) (2010) 1229–1235.

[4] L. Wang, Q. Du, Y. Yang, The study on fault diagnosis technology for intelligent device by BP neural network, Sci. Technol. Eng. 11(6) (2011) 1344–1347.

[5] K.G. Narendra, V.K. Sood, K. Khorasani, R. Patel, Application of a radial basis function (RBF) neural network for fault diagnosis in a HVDC system, IEEE Trans. Power Syst. 13(1) (1998) 177–183.

[6] M. Ge, R. Du, G. Zhang, Y. Xu, Fault diagnosis using support vector machine with an application in sheet metal stamping operations, Mech. Syst. Sig. Process. 18(1) (2004) 143–159.

[7] L.V. Ganyun, C. Haozhong, D. Lixin, Z. Haibao , Fault diagnosis of power transformer based on multi-layer SVM classifier, Electr. Power Syst. Res. 74(1) (2005) 1–7.

[8] F.E.H. Tay, L. Shen, Fault diagnosis based on rough set theory, Eng. Appl. Artif. Intell. 16(1) (2003) 39–43.

[9] Y. Ni, J. Zhou, B. Li, Method of fault diagnosis for power transform based on rough set theory, Control Decision 19(8) (2004) 943–946.

[10] M. Rode, G. Arhonditsis, D. Balin, T. Kebede, V. Krysanova, A. van Griensven, S. van der Zee, New challenges in integrated water quality modelling, Hydrol. Processes 24 (2010) 3447–3461.

[11] L. Marshall, D. Nott, A. Sharma, Hydrological model selection: A Bayesian alternative, Water Resour. Res. 41(10) (2005) 10422–10422.

[12] D.J. Spiegelhalter, N.G. Best, B.P. Carlin, A. Vander Linde, Bayesian measures of model complexity and fit, J. Royal Stat. Soc. Ser. B (Stat. Method.) 64(4) (2002) 583–639.

[13] Y. Liu, P.J. Yang, C. Hu, H.C. Guo, Water quality modeling for load reduction under uncertainty: A Bayesian approach, Water Res. 42 (2008) 3305–3314.

[14] A. Patil, Z.Q. Deng, Bayesian approach to estimating margin of safety for total maximum daily load development, J. Environ. Manage. 92 (2011) 910–918.

[15] I. Alameddine, S.S. Qian, K.H. Reckhow, A Bayesian changepoint-threshold model to examine the effect of TMDL implementation on the flow-nitrogen concentration relationship in the Neuse River basin, Water Res. 45 (2011) 51–62.

[16] B. Cai, Y. Liu, Z. Liu, X. Tian, Y. Zhang, R. Ji, Application of Bayesian networks in quantitative risk assessment of subsea blowout preventer operations, Risk Anal. 33(7) (2013) 1293–1311.

[17] B. Cai, Y. Liu, Y. Zhang, Q. Fan, S. Yu, Dynamic Bayesian networks based performance evaluation of subsea blowout preventers in presence of imperfect repair, Expert Syst. Appl. 40 (2013) 7544–7554.

[18] B. Cai, Y. Liu, Z. Liu, X. Tian, X. Dong, S. Yu, Using Bayesian networks in reliability evaluation for subsea blowout preventer control system, Reliab. Eng. Syst. Saf. 108 (2012) 32–41.

[19] B. Cai, Y. Liu, Q. Fan, Y. Zhang, Z. Liu, S. Yu, R. Ji, Multi-source information fusion based fault diagnosis of ground-source heat pump using Bayesian network, Appl. Energy 114 (2014) 1–9.

[20] Z. Li, J. Zhu, X. Shen, C. Zhang, J. Guo, Fault diagnosis of motor bearing based on the Bayesian network, Procedia Eng. 16 (2011) 18–26.

[21] F. Sahin, M. Yavuz, Z. Arnavut, Ö. Uluyol, Fault diagnosis for airplane engines using Bayesian networks and distributed particle swarm optimization, Parallel Comput. 33 (2007) 124–143.

[22] S. Li, H. Xie, Y. Guo, Engineering practice of modified A^2/O process, Tech. Equip. Environ. Pollut. Control 7 (5) (2006) 132–134.

[23] State Environmental Protection Administration of China, Discharge standard of pollutants for municipal wastewater treatmentplant of China, (GB 18918–2002), (2003) 5. Available at http://www.doc88.com/p-1186072804853.html.

[24] E. Richard, Neapolitan, Chapter 6—Further Properties of Bayesian Networks, Networks, Probabilistic Methods for Bioinformatics, (2009) 135–156.

[25] E. Richard, Neapolitan, Chapter 7—Learning Bayesian Network Parameters, Networks, Probabilistic Methods for Bioinformatics (2009) 157–175.
[26] E. Richard Neapolitan, Chapter 8—Learning Bayesian Network Structure, Networks, Probabilistic Methods for Bioinformatics (2009) 177–222.
[27] C.H. Sun, J. Cheng, Risk assessment of river water quality under accidental pollution based on Bayesian networks, Environ. Sci. 30(1) (2009) 47–51.
[28] D. Li, H.Z. Yang, X.F. Liang, Prediction analysis of a wastewater treatment system using a Bayesian network, Environ. Modell. Software 40 (2013) 140–150.