

A Bayesian Network Approach for Human Reliability Analysis of Power System

Junxi Tang, Yingkai Bao, Licheng Wang,
Haibo Lu, Yue Wang, Chuangxin Guo
College of Electrical Engineering
Zhejiang University
Hangzhou, China
E-mail: zjutangjx@163.com

Jia Liu, Bin Zhou
Maintenance Branch Company
Chongqing Electric Power Corporation
Chongqing, China

Abstract—Along with the improvement of equipment reliability, human error has become a great threat to the power system reliability and safety. However, the research of human reliability analysis in power system is still in its infancy. There is still little approach for quantitatively measuring the human reliability of power system. In this paper, the definition of human reliability of power system and a human error causal framework are given firstly. Secondly, with the suitable Performance Influencing Factors (PIFs) selected, the probability inference model based on Bayesian network for human reliability analysis is proposed. Finally, a case study shows that the proposed methodology can integrate organizational factors, situational factors, and individual factors to quantitatively measure the human reliability of power system. This approach provides forceful support for improving the human reliability of power system and has a good prospect.

Keywords—power system operation; human reliability; Bayesian network; probability

I. INTRODUCTION

Power system reliability is always one of the most concerned problems for researchers^[1]. With continuous improvement of automation, the dispatching automation system is developing to the intelligent direction. On the other hand, in the promotion of smart grid, the applications of automation technology and intelligent electronic device are improving the equipment reliability^[2]. At the same time, the problem of human reliability in power system has been showing up^[3]. Statistics show that in today's world more than 85% of industrial accidents put the blame on human factors^[4]. Moreover, for the American Electric Power Company, 96% of the accidents which lead to more than 8-days off work, are related with human unsafe behavior^[5]. Human error, as an important influencing factor, has become a great threat to the power system reliability and safety.

The research of human reliability analysis (HRA) can date back to the 1950s. After decades of development, there has been a deep understanding of human error mechanism in academic circles and dozens of human reliability analysis methods have been proposed^[6]. Human reliability analysis has been widely used in nuclear power

plants, aerospace and other industries with high security requirements. However, although human reliability analysis is so important, the research of HRA in power system is still in its infancy. Besides, there are several limitations in the existing human reliability analysis methods, such as emphasizing qualitative research but lack of quantitative analysis, insufficient account of the influencing factors, unrealistic independence assumption of factors leading to double counting^[8].

The purpose of this paper is to develop a Bayesian network approach for human reliability analysis to overcome the limitations of existing methods and analyze the human reliability of power system. Based on probabilistic analysis and graph theory, Bayesian network is one of the most efficient models in uncertain knowledge and reasoning field. Especially in the analysis of complex causal relationship, Bayesian network has a unique advantage^[9]. Therefore, it is used in this paper to show the relationship among the influencing factors of human error. In the following sections, the concepts in HRA and the human error causal framework are given in section II. After that, the probability inference model based on Bayesian network for human reliability analysis is proposed in section III. Section IV presents a case study to show the merit of the proposed methodology.

II. HUMAN ERROR CAUSAL FRAMEWORK & PIF SELECTION

A. Concepts in HRA

Human error means that something not intended or led the task outside its acceptable limits has been done by human. James Reason regards that human error is not a cause, but a consequence. Human errors are shaped and provoked by the upstream workplace and organizational factors^[11]. With reference to the definition of traditional equipment reliability, the human reliability of power system can be defined as the probability that a person correctly performs system-required activities in a required time period and working conditions.

B. Human Error Causal Framework

The study of human error mechanism is an important foundation for human reliability analysis. Researchers introduce organizational management, psychology, cognitive science and other disciplines to analyze the mechanism of human errors. The factors causing human

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error mainly consist of organizational factors, team factors, situational factors, individual factors, and so on.

The human error causal framework describes the causal mechanisms of human error occurring during the operation of power grid. As shown in Fig.1, in this human error causal framework, the factors influencing human reliability will be divided into three categories: organizational factors, situational factors, and individual factors. The organizational factors, mainly related to the problems of management activities and organizational processes, consist of organizational structure, task management, procedures quality, resource allocation, quality of training and so on. Generally, organizational factors affecting situational factors to cause an effect to human reliability. But sometimes they will have a direct impact on individual factors to raise the possibility of operator error. Situational factors are determined by the context and environmental conditions during the process of operation. Roughly situational factors should contain the following several aspects: workload, available time, work environment, equipment condition and quality of man-machine interface. Individual factors are determined by the operator's physiological state, psychological state, skill level and experience level. Individual factors, being the direct cause of human error, have the most direct impact on human reliability.

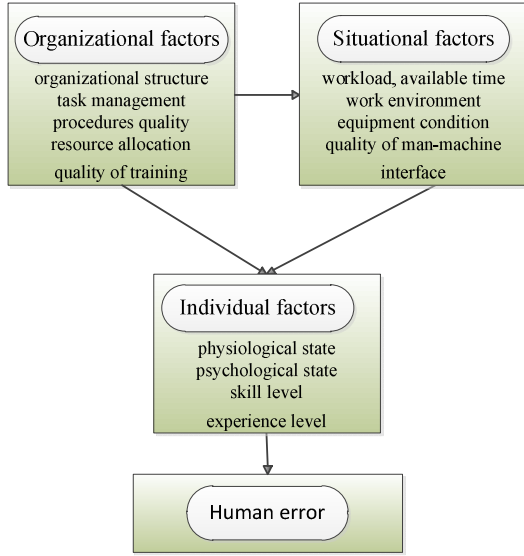


Fig.1 The diagram of human error causal framework

C. PIF Selection

The first task of human reliability analysis is to find out a set of human factors related to the operation performance. Consequently, the study of the Performance Shaping Factors (PSFs) was involved. PSFs were proposed by Swain in 1983 when he and Guttman built Technique for Human Error Rate Prediction (THERP) for qualitative and quantitative analysis of human reliability. The concept of PSFs was used for reference in many HRA methods. Since the 1990s, there have been a lot of discussions about developing PSFs into PIFs to make it more precise. PIFs are used to represent the situational contexts and causes affecting human performance in different systems^[12].

Because human reliability is influenced by a large number of different factors, it is very difficult to consider all the PIFs. What's more, PIFs are not independent of

each other, it is necessary to make a selection of PIFs in order to avoid the possibility of double counting. For different methods, analytical purposes and scenes, the PIFs will be selected differently. Considering characteristics of the grid and Bayesian network, the general requirements of selecting PIFs are summarized as follows:

- The PIFs with major impact should be covered as much as possible.
- The PIFs which are the root nodes of Bayesian network should be independent of each other.
- The same class of PIFs should also be independent as far as possible.
- The selected PIF should be measurable or evaluable.

According to the selection requirements, taking into account the size of model, some simplifications are made appropriately. The PIFs chosen for the HRA model are shown in Table I.

TABLE I. PERFORMANCE INFLUENCING FACTORS

PIFs	Explanations
Task Scheduling	The type, importance and complexity of task
Operational Procedure	The logical structure, detail, complexity, completeness and terminology definition of the operational procedure or operation order
Training Quality	Training methods, professional standards and evaluation, etc
Personnel Arrangement	The number, professionalism, qualification and status of personnel, the quality of cooperation, etc
Available Time	The available time for operator to complete the task
Work Load	Work intensity, complexity, the number of targets to be completed at the same time and consequences of failure
Work Environment	The temperature, light, noise and external disturbance of the workplace
Equipment Operability	The stability, recognizability, usability, accessibility and so on of the equipment
Pressure	Stress caused by the work load and time limitation
Attention	The operator's attention level to the current task
Skill & Experience	Operator's professionalism, knowledge, skills and experience levels

III. BAYESIAN NETWORK APPROACH TO HUMAN RELIABILITY ASSESSMENT

A. Bayesian Modeling Fundamentals

Bayesian network, combining causal knowledge and probabilistic knowledge, is one of the most efficient models in the uncertain knowledge and reasoning field^[13]. The network is composed of nodes and directed edges. The node-set $V = \{V_1, V_2, \dots, V_N\}$ represent the variables of interest while the directed edges representing causal relations among the variables. For a directed edge, the start node V_i is called parent node and the end node V_j is called child node. The root nodes are the nodes without any parent nodes. If the probabilities associated with every root node and the conditional probabilities associated with each intermediate child node are given, the probability distributions of child nodes are able to be calculated. The joint probability distribution is:

$$P(V) = P(V_1, V_2, \dots, V_N) = \prod_{i=1}^N P(V_i | F_{\text{parents}}(V_i)) \quad (1)$$

Here, $F_{\text{parents}}(V_i)$ is the set of parents of node V_i .

For a variable V_i which has m states, we can assume that the evidences $U = (V_1, \dots, V_{i-1}, V_{i+1}, \dots, V_N)$ of all nodes except node V_i are found, and then the posterior probability is:

$$P(V_i = V_{ij} | U) = \frac{P(V_i = V_{ij}, U)}{P(U)} = \frac{P(V_i = V_{ij}, U)}{\sum_{k=1}^m P(V_i = V_{ik}, U)} \quad (2)$$

B. Bayesian Networks Modeling of PIFs

As previously stated, human errors are provoked by organizational factors, situational factors, and individual factors. All these factors are represented by PIFs. Considering the characteristics of the operation task in the power system, a Bayesian network model for HRA in the grid is built with the selected PIFs.

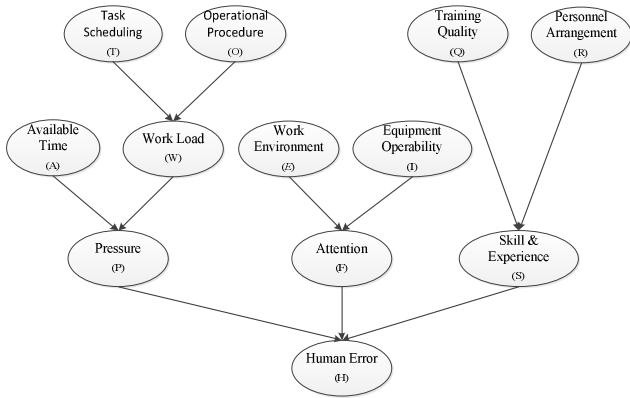


Fig.2 The Bayesian network model for HRA in the power grid

As shown in Fig.2, task scheduling, operational procedure, training quality and personnel arrangement are belong to organizational factors, while available time, work load, work environment, equipment operability belonging to situational factors. And, pressure, attention, skills and experience are part of the individual factors.

C. Bayesian Analysis

According to statistical data and the results of investigation or expert assessment, the probabilities associated with each node can be acquired. Then, based on the Bayesian network model as shown in Fig.2, causal inference and diagnostic analysis can be discussed.

1) Causal Inference

An assumption can be made that each factor has three states. For example, there are three states of factor “Work Environment (E)”: unfavorable(E_1), acceptable(E_2) and appropriate (E_3). Analogously, the factor “Equipment Operability (I)” has three states: negative (I_1), acceptable (I_2) and positive (I_3) while the states of factor “attention (F)” distributed into low(F_1), moderate(F_2) and high(F_3). With the probabilities of the root nodes (“Work

Environment” and “Equipment Operability”) and the conditional probabilities of the intermediate child node (“Attention”), the probability of “low” state of factor “Attention” is:

$$P(F = F_1) = \sum_{i=1}^3 P(E = E_i) \times \left[\sum_{j=1}^3 \frac{P(I = I_j)}{P(F = F_1 | E = E_i, I = I_j)} \right] \quad (3)$$

Similarly, the probabilities of “moderate” and “high” states of factor “Attention” are:

$$P(F = F_2) = \sum_{i=1}^3 P(E = E_i) \times \left[\sum_{j=1}^3 \frac{P(I = I_j)}{P(F = F_2 | E = E_i, I = I_j)} \right] \quad (4)$$

$$P(F = F_3) = \sum_{i=1}^3 P(E = E_i) \times \left[\sum_{j=1}^3 \frac{P(I = I_j)}{P(F = F_3 | E = E_i, I = I_j)} \right] \quad (5)$$

Thus the discrete probability distribution of factor “Attention” is acquired. In the same way, we can get the discrete probability distributions of all factors and finally get the human reliability.

2) Diagnostic Analysis

The diagnostic analysis is a bottom-up inference process that based on a Bayesian network model. According to evidences had known, the reasons causing certain consequence will be analyzed and the probabilities will be calculated. In this paper, there are two states of “Human Error(H)” in the Bayesian network model: normal(H_1) and error(H_2). Their probabilities can be computed from the causal inference. If assuming that human error has happened, we can get that $H = H_2$. Under this condition, according to Eq.(2), the posterior probability of “unfavorable” state of factor “Work Environment” is:

$$\begin{aligned} P(E = E_1 | H = H_2) &= \frac{P(E = E_1, H = H_2)}{P(H = H_2)} \\ &= \frac{P(E = E_1) \times P(H = H_2 | E = E_1)}{P(H = H_2)} \end{aligned} \quad (6)$$

Similarly, the posterior probabilities of all the root nodes can be calculated.

IV. APPLICATION

In this example, the proposed Bayesian network approach for human reliability analysis is applied to analyze the second case in reference [10]. The case is that the substation transmission line failure occurred due to lightning in the midnight. After the circuit breaker tripping, emergency responding operation is need. With the operation order generated, the switching operation is carried out by two operators. One man is in charge of monitoring while the other man being responsible for operating. In this case, one reliability assessment expert and one operation manager were invited to evaluate the operation. As a result, the probabilities associated with every root node and the conditional probabilities

associated with each intermediate child node were acquired. The conditional probabilities of node “Attention” are as shown in Table II. The probabilities tables of other nodes can be found in the Appendix.

TABLE II. CONDITIONAL PROBABILITY OF NODE “ATTENTION”

Nodes	Work Environment (E)	Equipment Operability (I)	Attention (F)		
			low (F_1)	moderate (F_2)	high (F_3)
States & Probabilities	unfavorable (E_1)	negative (I_1)	0.9	0.09	0.01
		acceptable (I_2)	0.8	0.15	0.05
		positive (I_3)	0.6	0.3	0.1
	acceptable (E_2)	negative (I_1)	0.4	0.5	0.1
		acceptable (I_2)	0.15	0.7	0.15
		positive (I_3)	0.1	0.5	0.4
	appropriate (E_3)	negative (I_1)	0.2	0.6	0.2
		acceptable (I_2)	0.1	0.2	0.7
		positive (I_3)	0.01	0.09	0.9

With the probability distributions of root nodes “Work Environment” and “Equipment Operability” as well as the conditional probabilities of node “Attention”, according to (1) and (3), the probability of “low” state of factor “Attention” is:

$$\begin{aligned}
 P(F=F_1) &= \sum_{i=1}^3 P(E=E_i) \times \left[\sum_{j=1}^3 P(I=I_j) \times P(F=F_1 | E=E_i, I=I_j) \right] \\
 &= 0.1 \times (0.1 \times 0.9 + 0.3 \times 0.8 + 0.6 \times 0.6) \\
 &\quad + 0.4 \times (0.1 \times 0.4 + 0.3 \times 0.15 + 0.6 \times 0.1) \\
 &\quad + 0.5 \times (0.1 \times 0.2 + 0.3 \times 0.1 + 0.6 \times 0.01) \\
 &= 0.155
 \end{aligned} \quad (7)$$

Similarly, $P(F=F_2)=0.3344$, $P(F=F_3)=0.5106$.

Here, we use Microsoft Bayesian Network Editor (MSBNx), an noncommercial software, to calculate the probabilities conveniently. The computation is shown in Fig.3.

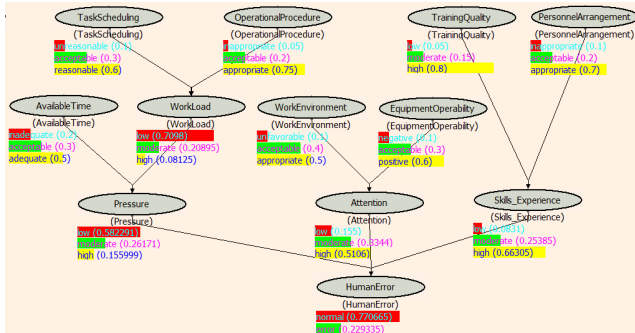


Fig.3 The Bayesian network model in MSBNx

In Fig.3, the human reliability can be found equal to 0.770665 and the probability of human error is 0.229335. Compared to the human error probability in reference [10] which is 0.2258 obtained with the Cognitive Reliability and Error Analysis Method (CREAM), the probability of human error calculated by approach in this paper is almost

the same but a little higher. It is because that there are more influencing factors including organizational factors considered in this model. It should be specially explained that human error includes the mistakes prevented by anti-misoperation devices or crews and not leading to severe outcomes.

Assuming that human error had happened, the posterior probabilities of all the root nodes can be calculated according to (2) with the Bayesian network. For example, the posterior probability of “unfavorable” state of the factor “Work Environment” is:

$$\begin{aligned}
 P(E=E_1 | H=H_2) &= \frac{P(E=E_1) \times P(H=H_2 | E=E_1)}{P(H=H_2)} \\
 &= \frac{0.1 \times 0.40567}{0.229335} \\
 &= 0.17689
 \end{aligned} \quad (8)$$

Also, the MSBNx is used to calculate the posterior probabilities of all root nodes conveniently. The computation result is shown in Fig.4.

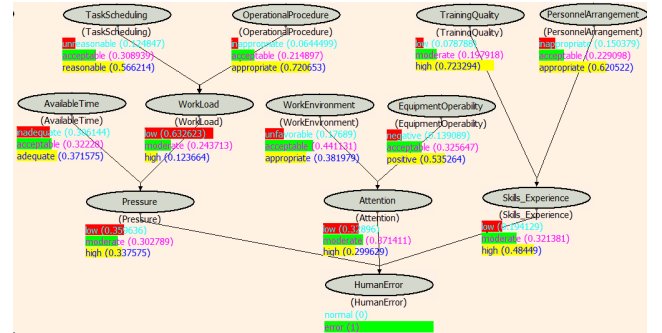


Fig.4 The Bayesian network model for diagnostic inference in MSBNx

TABLE III. PRIOR PROBABILITIES AND POSTERIOR PROBABILITIES OF ROOT NODES

Root nodes	States	Prior Probabilities	Posterior Probabilities
Available Time	inadequate	0.2	0.3061
Task Scheduling	unreasonable	0.1	0.1248
Operational Procedure	inappropriate	0.05	0.0644
Work Environment	unfavorable	0.1	0.1769
Equipment Operability	negative	0.1	0.1391
Training Quality	low	0.05	0.0788
Personnel Arrangement	inappropriate	0.1	0.1504

Table III shows the prior and posterior probabilities of root nodes respectively. It can be noted that there are significant changes in the occurrence probabilities of work environment being unfavorable, training quality being low, available time being inadequate and personnel arrangement being inappropriate when human error happened. It might suggest that the work environment, training quality, available time and personnel arrangement are significant influencing factors to human reliability.

Consequently, in order to avoid human errors, more attention should be paid to improve the working condition and quality of training. Besides, it is important to give enough time for the operators to carry out operant activities. And reasonable crew resource management is needed. If hitting a complex situation, the supervisor or technical director should take charge of the matters when necessary. With the diagnostic analysis, we can identify some major factors that have a great impact on human reliability. Hence, some improvements can be made for the prevention of human error.

V. CONCLUSION

Human error has become an important factor influencing the power system reliability and safety. However, the human reliability analysis of power system is still in the stage of introducing. This paper proposes a Bayesian network approach to quantitatively measure the human reliability of power system. Compared with the traditional HRA methods, the approach presented in this paper overcomes three major limitations of existing methods: lack of quantitative analysis, insufficient account of the influencing factors and the problem of double counting. A case example shows that the proposed methodology can integrate organizational factors, situational factors, and individual factors to quantitatively measure the human reliability of power system. Moreover, according to the diagnostic analysis, the most significant factors leading to human error can be identified, and some improvements can be made for the prevention of human error. This approach provides forceful support for improving the human reliability of power system and has a good prospect.

APPENDIX

TABLE IV. PRIOR PROBABILITIES OF ROOT NODES

Root Nodes	States	Probabilities
Available Time	inadequate	0.2
	acceptable	0.3
	adequate	0.5
Task Scheduling	unreasonable	0.1
	acceptable	0.3
	reasonable	0.6
Operational Procedure	inappropriate	0.05
	acceptable	0.2
	appropriate	0.75
Work Environment	unfavorable	0.1
	acceptable	0.4
	appropriate	0.5
Equipment Operability	negative	0.1
	acceptable	0.3
	positive	0.6
Training Quality	low	0.05
	moderate	0.15
	high	0.8
Personnel Arrangement	inappropriate	0.1
	acceptable	0.2
	appropriate	0.7

TABLE V. CONDITIONAL PROBABILITY OF NODE "WORK LOAD"

Nodes	Task Scheduling	Operational Procedure	Work Load		
			low	moderate	high
States & Probabilities	unreasonable	inappropriate	0.01	0.09	0.9
		acceptable	0.05	0.15	0.8
		appropriate	0.2	0.6	0.2
	acceptable	inappropriate	0.05	0.15	0.8
		acceptable	0.1	0.8	0.1
		appropriate	0.8	0.15	0.05
	reasonable	inappropriate	0.2	0.6	0.2
		acceptable	0.8	0.15	0.05
		appropriate	0.9	0.09	0.01

TABLE VI. CONDITIONAL PROBABILITY OF NODE "PRESSURE"

Nodes	Available Time	Work Load	Pressure		
			low	moderate	high
States & Probabilities	inadequate	high	0.01	0.09	0.9
		moderate	0.05	0.15	0.8
		low	0.2	0.5	0.3
	acceptable	high	0.1	0.3	0.6
		moderate	0.1	0.7	0.2
		low	0.6	0.3	0.1
	adequate	high	0.3	0.5	0.2
		moderate	0.8	0.15	0.05
		low	0.9	0.09	0.01

TABLE VII. CONDITIONAL PROBABILITY OF NODE "SKILL & EXPERIENCE"

Nodes	Training Quality	Personnel Arrangement	Skill & Experience		
			low	moderate	high
States & Probabilities	low	inappropriate	0.9	0.09	0.01
		acceptable	0.7	0.2	0.1
		appropriate	0.2	0.6	0.2
	moderate	inappropriate	0.7	0.2	0.1
		acceptable	0.2	0.6	0.2
		appropriate	0.1	0.6	0.3
	high	inappropriate	0.2	0.6	0.2
		acceptable	0.1	0.3	0.6
		appropriate	0.01	0.09	0.9

TABLE VIII. CONDITIONAL PROBABILITY OF NODE “HUMAN ERROR”

Nodes	Pressure	Attention	Skill & Experience	Human Error	
				normal	error
States & Probabilities	low	low	low	0.3	0.7
			moderate	0.5	0.5
			high	0.7	0.3
		moderate	low	0.5	0.5
			moderate	0.8	0.2
			high	0.9	0.1
		high	low	0.7	0.3
			moderate	0.9	0.1
			high	0.99	0.01
	moderate	low	low	0.8	0.2
			moderate	0.4	0.6
			high	0.5	0.5
		moderate	low	0.3	0.7
			moderate	0.6	0.4
			high	0.8	0.2
		high	low	0.5	0.5
			moderate	0.8	0.2
			high	0.9	0.1
	high	low	low	0.01	0.99
			moderate	0.1	0.9
			high	0.3	0.7
		moderate	low	0.2	0.8
			moderate	0.4	0.6
			high	0.5	0.5
		high	low	0.3	0.7
			moderate	0.5	0.5
			high	0.7	0.3

REFERENCES

- [1] GUO Yongji, “Reliability of power systems and power equipment,” *Automation of Electric Power Systems*, vol. 25, pp.53-56, Sep. 2001.
- [2] MA Taotao, GUO Chuangxin, CAO Yijia, HAN Zhenxiang, QIN jie and ZHANG Wangjun, “Current status and development trend of intelligent dispatching automation system of power system,” *Automation of Electric Power Systems*, vol.34, pp.7-11, May. 2010.
- [3] ZHANG Jingjing, DING Ming, LI Shenghu, “Impact analysis of human error on protection system reliability,” *Automation of Electric Power Systems*, vol.36, pp.1-5, Apr. 2012.
- [4] Zhang Li, Wang Yiqun, Huang Shudong, “System Model for Preventing in Depth the Accident due to Human Factor,” *China Safety Science Journal*, vol.12, pp.34-37, Feb. 2002.
- [5] LING Yi, ZHANG Yongjun, LI Zhe and CAI zexiang, “Analysis of electric operation error accident in substation based on the principle of causal relation of accident,” *Relay*, vol. 35, pp.55-58, Aug. 2007.
- [6] HE Xuhong, GAO Jia, HUANG Xiangrui, “Comparison of human reliability analysis methods,” *Nuclear Power Engineering*, vol.26, pp.627-630, Dec. 2005.
- [7] GUO Chuangxin, LU Haibo, YU Bin and MA Taotao, “A survey of research on security risk assessment of secondary system,” *Power System Technology*, vol. 37, pp.112-118, Jan. 2013.
- [8] Li Pengcheng, CHEN Guohua, DAI Licao and ZHANG Li, “A fuzzy Bayesian network approach to improve the quantification of organizational influences in HRA frameworks,” *Safety Science*, vol.50, pp.1569-1583, Apr. 2012.
- [9] WU Xin, GUO Chuangxin, CAO Yijia, “A new fault diagnosis approach of power system based on bayesian network and temporal order information,” *Proceedings of the CSEE*, vol.25, pp.14-18, Jul. 2005.
- [10] LU Haibo, WANG Mei, GUO Chuangxin and YU Bin, “A quantitative method for human reliability in power system based on CREAM,” *Power System Protection and Control*, vol. 41, pp.37-42, Mar. 2013.
- [11] Reason J, *Human error*. UK.Cambridge: Cambridge university press, 1990.
- [12] Groth K M and Mosleh A, “A data-informed PIF hierarchy for model-based human reliability analysis,” *Reliability Engineering and System Safety*, vol.108, pp.154-174, Dec. 2012.
- [13] Przytula K.W. and Thompson D., “Construction of Bayesian networks for diagnostics,” *IEEE Aerospace Conference Proceedings*, vol.5, pp.193-200, Mar. 2000.
- [14] XIE Kaigui, JI Jing, CAO Kan, GAN Ming and HU Bo, “Review of influencing factors for bulk power systems reliability,” *Power System Protection and Control*, vol.39, pp.149-154, Dec. 2011.
- [15] Musharraf, M., Hassan, J., Khan, F., Veitch, B., MacKinnon, S. and Imtiaz, S., “Human reliability assessment during offshore emergency conditions,” *Safety Science*, vol.59, pp.19-27, Apr. 2013.