Reliability Analysis of Gasifier Lock Bucket Valve System Based on DBN Method

Ming Liu, Jiayue Ma, Yili Duo, and Tie Sun

1School of Environment and Safety Engineering, Liaoning Petrochemical University, Fushun 113001, China
2School of Mechanical Engineering, Liaoning Petrochemical University, Fushun 113001, China

Correspondence should be addressed to Ming Liu; liuming1075@163.com

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In order to solve the problem of zero-failure data and dynamic failure in gasification system, a dynamic Bayesian network (DBN) combined with Monte Carlo simulations is proposed to analyze the reliability of the gasifier lock bucket valve system. On the basis of studying the structure of the gasifier lock bucket valve system, the reliability model of the system is built based on DBN, and the structure learning is realized. The Monte Carlo simulation is used for the timed ending test in Bayesian estimation, which effectively solves the problem of zero-failure data and realizes the parameter learning. Through the Metropolis-Hastings (M-Hs) algorithm, the prior distribution of dynamic node is randomly sampled to obtain the target distribution, which makes the reliability predictive inference for DBN of the gasifier lock bucket valve system faster and more accurate. The obtained reliability prediction is a curve varying with time. The results show that the valve frequent switch node of DBN of the gasifier lock bucket valve system is identified as the weak link by the powerful reverse inference for DBN, which needs to be paid more attention to. This method can effectively improve the maintenance level of the gasifier lock bucket valve system and can effectively reduce the possibility of accidents.

1. Introduction

The development of the modern coal chemical industry makes modern coal gasification technology develop towards high temperature, pressure gasification, large scale, and diversification. The success of coal gasification technology selection is directly related to the long-term stable operation of coal chemical production unit [1]. Both coal water slurry gasification and pulverized coal gasification have been commercialized. In particular, SE gasification technology showed great advantages over traditional gasifiers in scaling up the installations, and it has the advantages of wide adaptability of coal, low consumption of raw materials, high carbon conversion rate, maturity, reliability, and so on. As shown in Figure 1, it is composed of coal preparation, high-pressure coal feed and transport, gasification and washing, and slag water treatment units. A high efficiency of carbon conversion of more than 99% was achieved. The technology has been combined with sulphur conversion, carbon dioxide capture, and integrated gasification combined cycle, which provides a total solution of environmental pollution in the use of coals and realizes the effective separation of fine ash from high ash coal in current industrial installations. Due to the high solid content in water and the great wear force on the spool, the leakage inside the scum lock valve needs to be replaced regularly, which is a technical problem in the industry. In the early stage, internal leakage happened in New Energy Phoenix Energy Co., Ltd., for failing to close the locking bucket pressure relief valve and the flushing water valve of bucket pressure relief pipeline. Gasifier lock bucket valve system is the core of the coal gasification unit, and its reliability study has guiding significance to ensure the safe and stable operation of the unit. Therefore, the research on the reliability of gasifier lock bucket valve system can provide an important theoretical basis for the reliability analysis of large coal gasification unit, and it is of great significance to quickly and effectively determine the weak links of gasification system. Thus, the research will not only improve the system design...
but also ensure the stable operation of gasification system and reduce the maintenance cost [2–4].

At present, the research on the reliability of systems using dynamic Bayesian network (DBN) is mainly in the case of known system failure data; observation data and hidden variables are discrete or subject to Gaussian distribution or by transforming fault tree model into DBN model. Ming Liu [5] applied Bayesian network to carry out static risk analysis on gasifier feeding system. Yuan Zhi [6] developed a probability estimation of dust explosions domino effect based on Bayesian networks. Leng David [7] presented a methodology to use deterministic steady-state process models to derive Bayesian networks based on alarm event detection. Khakzad Nima [8] used imprecise probabilities in Bayesian network. In order to solve the problem of risk and reliability evaluation of systems with redundant equipment, O’Connor Andrew [9] proposed a reliability evaluation method based on Bayesian network. Zarei Esmaeil [10] proposed a method combining Bow-tie diagram with Bayesian network to evaluate the security of dynamic systems. Scutari Marco [11] used DBN model to process incomplete and dynamic data. Zhi Jiang Mei [12] introduced a DBN model to facilitate the estimation of the dynamic emergency risk in sea lanes. Khakzad Nima [13, 14] and Xian Guo Wu [15] analyzed the reliability of the system based on the known system parameters and the method of transforming the fault tree model into a DBN model. S Montani [16] proposed the method of transforming dynamic fault tree into DBN.

However, there are relatively few research studies on DBN with zero-failure data, continuous non-Gaussian observation data, and hidden variable data. Therefore, a method of DBN combined with Monte Carlo simulations is put forward to dynamically analyze the reliability of gasifier lock bucket valve system under zero-failure data. The dynamic reliability analysis of zero-failure data system is solved. The Metropolis-Hastings (M-Hs) algorithm amplifies acceptance rate $\alpha$ and contributes to the fast convergence of Markov chains. For analyzing DBN of continuous system, using M-Hs algorithm to discretize the prior distribution of dynamic node, inference for DBN can get faster and more accurate results.

2. Theoretical Basis for DBN and M-Hs Algorithm

2.1. Introduction of DBN. DBN is an extension of static Bayesian network on the time dimension; in other words, the constraint of time attribute is added into the original network structure to reflect the dynamic change trend of variables [13, 14]. DBN can efficiently process the timing information of the system based on the hidden Markov model. The initial network $B_0$ and transition network $B_\Delta$ must be defined first.

The distribution probability of the current initial state can be expressed as

$$P(X[0]) = \prod_{i=1}^{N} P(X_i^0|Pa(X_i^0)).$$

(1)

Between $t$ and $t + \Delta t$ moment, the state transition probability is given as the following functional form:

$$P(X[t + \Delta t]|X[t]) = \prod_{i=1}^{N} P(X_i^{t+\Delta t}|Pa(X_i^{t+\Delta t})).$$

(2)

Similarly, the joint distribution of any node in DBN can be derived as presented as follows:
2.2. DBN Learning. DBN learning includes network structure learning and parameter learning. The establishment of network structure mainly includes four ways: graphic element transformation modeling, using expert knowledge to model manually, learning modeling, and mixed modeling. Parameter learning mainly includes prior probability of parent node and conditional probability, and its prior distribution algorithm mainly includes maximum likelihood estimation method, Bayesian estimation method, and maximum expectation algorithm [18].

For solving DBN, the key lies in the establishment of conditional probability, and the conditional probability is divided into two kinds, the first is the static conditional probability of child node in the same time slice, and the second is conditional transition probability of transition network between different time slices. For the same time slice, the relationship between parent and child node is mainly the logical relationship of AND and OR, the establishment of the conditional probability of child node is relatively simple, and thus, it will not be described in detail. The conditional transition probability of dynamic node is mainly based on hidden Markov process. When the event only has two states of normal and failure, the conditional transition probability of dynamic node is expressed as

\[
P(X_i(t + \Delta t) = 0|X_i(t) = 0) = 1 - \int_t^{t+\Delta t} f_x(t) dt,
\]

\[
P(X_i(t + \Delta t) = 1|X_i(t) = 0) = \int_t^{t+\Delta t} f_x(t) dt,
\]

\[
P(X_i(t + \Delta t) = 0|X_i(t) = 1) = \int_t^{t+\Delta t} g_x(t) dt,
\]

\[
P(X_i(t + \Delta t) = 1|X_i(t) = 1) = 1 - \int_t^{t+\Delta t} g_x(t) dt,
\]

where \(X_i = 0\) represents that node \(X_i\) is in the nonoccurring state, \(X_i = 1\) represents that node \(X_i\) is in the occurring state; \(f_x(t)\) is the failure probability density function of node \(X_i\), and \(g_x(t)\) is the maintenance density function of node \(X_i\) [19].

2.3. Inference for DBN. The main purpose of inference for DBN is to reason about the probability of the maximum possible value of the hidden variable based on a large amount of observed data [20]. The observed data are the basis of inference. Observation data can be divided into discrete observation data and continuous Gaussian observation data, and hidden variables can also be divided into discrete data [21, 22] and continuous Gaussian data [12]. In this paper, the observed data and the hidden variables are not Gauss state; therefore, the M-Hs sampling in Monte Carlo simulations is used to discretize them first, and then the reliability probability of the whole system is calculated, MATLAB R2018a programming language combined with FullBNT toolbox to achieve automatic solution.

2.4. Introduction of M-Hs Algorithm. Markov Chain Monte Carlo (MCMC) combines the modeling capabilities of Markov methods with the computational capabilities of Monte Carlo simulations. It is an effective tool to deal with complex statistical problems and often used in the field of Bayesian analysis for complex high-dimensional integral operations. MCMC can always obtain a convergent Markov chain, and the limit distribution of the chain will be the desired target distribution.

M-Hs algorithm is the core of MCMC, of which the idea is to construct a Markov chain featuring an invariant target distribution \(\pi(\theta)\) and target distribution. According to Bayesian theory, for a given set of \(t\) data sets, the general structure is as follows:

\[
\pi(\theta|t) \propto L(t|\theta)p(\theta),
\]

where \(L(t|\theta)\) is the likelihood function of the \(t\) data sets with known parameters, which depends on the function form of the selected model; \(p(\theta)\) is the prior distribution of parameters; \(L(\cdot|\cdot)\) and \(p(\cdot)\) are assumed to be known functions; the proportionality notation indicates that the target distribution \(\pi(\theta|t)\) is proportional to its normalization factor.

Markov chains randomly select \(\theta^j\) as the initial value. The chain sequence \(\theta^1, \theta^2, \theta^3, \ldots, \theta^q\) is generated by an appropriate kinetic equation \(K(\theta'|\theta)\), which can generate new proposal values from the previous value. In practice, symmetric \(K(\theta'|\theta)\) is often used, which makes \(K(\theta'|\theta) = K((\theta|\theta'))\). Metropolis et al. made the same choice in their original algorithm and asymmetric dynamics are summarized by Hastings.

Here, \(K(\theta'|\theta)\) is also called the proposal distribution, and it should be selected as close to the target distribution as possible.

In the \(j\)th chain iteration, if \(\theta^j\) is known, it is generally assumed that the proposal value \(\theta^j\) becomes the new \(\theta^j+1\) value in the chain with a probability, where \(a\) is given as the following functional form:

\[
a = \min \left\{ 1, \frac{\pi(\theta^j|t) \cdot K(\theta^j|\theta^j)}{\pi(\theta^j|t) \cdot K(\theta^j|\theta^j)} \right\}.
\]

Otherwise, the proposal value \(\theta^j\) will be discarded, and the new proposal value \(\theta^j+1\) will be equal to the previous proposal value; that is to say, \(\theta^j+1 = \theta^j[23–28]\).
3. Case Studies

3.1. Construction of DBN for the Gasifier Lock Bucket Valve System. For familiar fields, the structure of DBN can be constructed with common sense and expert knowledge, while for less familiar fields, the algorithm of mining network structure from mass data is used. This paper is based on expert knowledge and is the failure rate of the gasifier lock bucket valve node is given by the expert knowledge and literature [29, 30]; the logic relationship between gasifier lock bucket valve system and events is obtained. At the same time, the time attribute is added to build the DBN for the gasifier lock bucket valve system, as shown in Figure 3, and the nodes in Figure 3 are described in Table 1 based on expert knowledge from the previous studies [2, 31–37].

3.2. Prior Parameters of DBN of the Gasifier Lock Bucket Valve System. According to the failure form of the parent nodes, the failure mode of each node of the gasifier lock bucket valve system follows exponential distribution, and the conditional probability distribution of the child node follows the Weibull distribution. In the case of zero-failure data of the gasifier lock bucket valve system, the prior parameter of the gasifier lock bucket valve node is given by the expert knowledge and is the failure rate of the gasifier lock bucket valve as $\lambda_I = 0.0002$. The prior parameters of other nodes are obtained by Monte Carlo simulation [23] combined with Bayesian estimation with zero-failure data [38–41]. Monte Carlo simulation is used in the timed ending test of Bayesian estimation. The following are the steps after adding Monte Carlo simulation to the timed ending test:

Step 1. Set $n$, $t_k$, and $t_i$, $i = 1, 2, 3, \ldots, k$; here, $0 < t_1 < t_2 < \ldots < t_k$.

Step 2. From the uniform distribution of $[0,1]$ random sampling $n$ times, the failure probability $p_n$ is obtained.

Step 3. If $p_n < p_k$, then the sample is reliable. The number of statistically reliable samples is called $n_j$. It is derived $S_j$ from

$$S_j = \sum_{i=j}^{k} n_i \quad j = 1, 2, 3, \ldots, k, \quad (7)$$

where $n$ is the number of samples per group; $t_k$ is the maximum duration of the timed ending test; $t_i$ is the time when the timed ending test stops; $i$ is the number of groups of samples; $p_k$ is the upper limit of failure probability; $S_j$ is the data sets of reliable samples of the system.

Since long-time operational performances show that the lifetime of IGSP burners is about 150–200 days [42], and thus, the experiment maximum duration is $t_k = 4000 h$ at the timed ending test, and the node state is observed at every 400 h interval. In Bayesian estimation, the upper bound of failure probability $P_k$ is the failure probability of gasifier lock bucket valve node at the time $t_k$, and thus, $P_k = 0.5507$. The data sets $S_j$ obtained from simulation are put into Bayes estimation to calculate the prior parameters except node $T$, and the calculated results are in Tables 2 and 3 according to Table 1.

Assuming that each node includes two states of work (0) and failure (1), the prior distribution of parent node of $X_1$ is randomly sampled by the direct sampling method. And the prior probability of parent node of $X_1$ is obtained as

$$P(X_1 = 0) = 0.965554,$$

$$P(X_1 = 1) = 0.034446. \quad (8)$$

Sampling time $t_0 = 301.619201 h$ is substituted into prior distributions of other nodes. The nodes in the gasifier lock bucket valve system are independent of each other, and thus, the conditional probability in the same time slice of child node can be obtained by means of OR gate logic relation and Bayes theorem [43]:

$$P(M | X_1, X_2, \ldots, X_n) = P(M | X_1). P(M | X_2) \ldots P(M | X_n). \quad (9)$$

3.3. Sampling by M-Hs Algorithm. In this paper, the dynamic nodes of the gasifier lock bucket valve system are $X_1, X_2, \ldots, X_{12}$. To highlight the changing trend of system reliability and the importance of the dynamic node, the maintenance factor is not considered in this part, so the maintenance density function is 0. According to (4) and Table 2, $t$ moment to $t + \Delta t$ conditional transition probability of dynamic node can be obtained as follows:
be found as dynamic nodes of the gasifier lock bucket valve system can

the following steps are required to generate posterior \( \vartheta \) for \( \vartheta \) using M-Hs algorithm:

Step 1. Select an initial guess of \( \vartheta \) and as \( \vartheta_0 \).

Step 2. Set \( t = 0, 1, 2, 3 \ldots T \).

Step 3. Generate \( \vartheta' \) using the proposal \( N(\vartheta_{t-1}, \sigma^2) \) distribution.

Step 4. Compute \( \alpha = \min\{1, \pi(\vartheta' | \vartheta) \cdot K(\vartheta' | \vartheta)^{-1}\pi(\vartheta | \vartheta') \cdot K(\vartheta' | \vartheta)^{1}\} \).

Step 5. Then, generate a sample \( u \) from the uniform distribution of \([0, 1]\).
Step 6. If \( u \leq \alpha \), accept the proposal and set \( \vartheta_t = \vartheta' \), else set \( \vartheta_t = \vartheta_{t-1} \).

Step 7. Repeat steps (3–6) \( T \) times and collect an adequate number of samples.

Taking X7 as an example, it can be seen from Table 2 that the failure rate of node X7 is \( \lambda_{X7} = 2.409631E - 4 \) and the number of iterations is set as \( 1E5 \). In Figure 4, the black dashed line is the posterior distribution after sampling of target distribution of X7, and the red solid line is the target distribution before sampling of X7. The target distribution after sampling is highly consistent with the target distribution before sampling in the early stage, and the accuracy of exact inference for DBN can be further improved through DBN updating. Figure 5 shows the convergence function curve of the Markov chain changing with the number of iterations and converges after \( 5E4 \sim 6E4 \) iteration. Figure 6 shows the target distribution PDF after sampling, which can accurately describe the curve of the probability density function of X7.

### 3.4. System Reliability Analysis

The dynamic prediction of the reliability change of the gasifier lock bucket valve system within 0–300 h is carried out. Take the number of time slices as 10, and then the time interval of each slice is 30 h. Based on the prior probability of parent nodes, the conditional probability of child nodes, and the conditional transition probability of dynamic nodes, the reliability prediction of the gasifier lock bucket valve system is obtained by the predictive inference for DBN. As shown in Figure 7, the reliability of the gasifier lock bucket valve system and its subsystems gradually decreases with the increase of time, and the decrease rate is in turn \( T > M2 > M1 \). The reliability prediction of the gasifier lock bucket valve system when maintenance factors are taken into account is shown in Figure 8. It can be seen that maintaining the system equipment can reduce the possibility of accidents occurring in the operation process, improve the reliability of the system, and extend the operation cycle of the equipment. The importance of maintenance measures for safe operation of equipment can be seen.

According to the powerful reverse inference for DBN, the failure probability of the node \( T \) of the gasifier lock bucket valve system is set as 1, the posterior probability of each node of the system is obtained, and the weak links are analyzed. After 1000 h of operation, prior probability, posterior probability, and their differences of parent nodes are compared, as shown in Figure 9. In order to improve the reliability of the gasifier lock bucket valve system, the order of attention of each node is \( X10 > X11 > X6 > X8 > X9 > X7 > X4 > X1 > X3 > X2 > X5 > X12 \). Nodes X6, X8, X10, and X11 have a great impact on system reliability, and X10 (valve frequent switch) is the weak link of the system.

In order to verify the feasibility and accuracy of the method proposed in this paper, GeNIe 2.1 software [26] is used to compare and analyze gasifier lock bucket valve system.

The conditional transition probability of dynamic nodes is obtained by (10). Taking dynamic node X1 as an example.
and making $\Delta t = 1$ h, the conditional transition probability of dynamic node $X_1$ from moment $t$ to $t + \Delta t$ is shown in Table 4.

The prior probability of parent nodes, the conditional probability of child nodes, and the conditional transition probability of dynamic nodes in Table 4 are input into the DBN model of the gasifier lock bucket valve system established by GeNiE 2.1. The result is shown in Figure 10.

The reliability solution results of the two methods at multiple time points are compared and analyzed as shown in Table 5. As can be seen from Table 5, as time goes by, the difference between the two methods fluctuates between 0.005 and 0.0106, with the maximum difference only being 0.010501, which verifies the feasibility of DBN combined with the Monte Carlo method proposed in this paper and has higher calculation accuracy. The calculation process of this paper can be shown in Figure 11.
Figure 10: DBN model of the gasifier lock bucket valve system created by GeNIe 2.1.

Table 5: Comparison of solution result.

|        | 30 h       | 120 h      | 210 h      | 300 h      |
|--------|------------|------------|------------|------------|
| DBN MC | 0.958255   | 0.836645   | 0.726281   | 0.623723   |
| GeNIe 2.1 | 0.953373 | 0.826144   | 0.715896   | 0.620365   |
| Difference value | 0.004881 | 0.010501   | 0.010385   | 0.003358   |

Figure 11: Technical route.
4. Conclusion

(1) The Monte Carlo simulation sampled the timed ending test in Bayesian estimation that the prior data of the gasifier lock bucket valve system can be obtained. M-Hs algorithm samples the prior distribution of dynamic nodes and gets the target distribution, which is highly consistent with the actual target distribution and provides an effective method to solve the change of conditional transition probability with time.

(2) The reliability analysis of gasifier lock bucket valve in two directions is carried out by the exact inference for DBN. The reliability variation trend of this system and the factors causing system failure can be obtained by predictive inference. Reverse inference for DBN of the system can be used to obtain the important attention sequence and the weak links of the nodes that cause the failure of the gasifier lock bucket valve system and the weak link is the valve frequent switch.

(3) Based on DBN and Monte Carlo simulation, reliability analysis of gasifier lock bucket valve system is carried out in this paper. The practical problems such as the difficulty of reliability analysis of dynamic system, zero-failure probability, and the inconformity of observed data and hidden variables with Gaussian distribution can be effectively solved by this method. The maximum difference between this method and GeNIe 2.1 is only 0.010501.

(4) This paper focuses on the monitoring and analysis of location and attribute information of workers and mechanical equipment, while in the aspect of microbehavior monitoring of workers and machinery, only a preliminary discussion is made, and further research is needed in the future.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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References

[1] L. Zhao and K. S. Gallagher, “Research, development, demonstration, and early deployment policies for advanced-coal technology in China,” Energy Policy, vol. 35, no. 12, pp. 6467–6477, 2007.

[2] C. A. D. Pozo, J. H. Cloete, S. Cloete, N. J. Lvaro, and S. Amini, “Integration of gas switching combustion in a humid air turbine cycle for flexible power production from solid fuels with near-zero emissions of CO2 and other pollutants,” International Journal of Energy Research, vol. 44, no. 9, pp. 7299–7322, 2020.

[3] J. W. Lee, S. W. Chung, S. O. Ryu et al., “Pneumatic transport characteristics of coarse size pulverized coal for the application of fast circulating fluidized bed gasification,” Korean Journal of Chemical Engineering, vol. 34, no. 1, pp. 54–61, 2017.

[4] S.-T. Tu, Y.-G. Zheng, and X.-C. Zhang, “Material challenges for long term and safe operation of coal gasification systems,” Energy Materials 2014, vol. 7, pp. 365–372, 2014.

[5] M. Liu, Y. Jin, K. Li, Y. L. Duo, and T. Sun, “Risk analysis on feeding system of gasifier based on Bayesian network,” China Work Safety Science and Technology, vol. 16, no. 6, pp. 87–92, 2020, (in Chinese).

[6] Y. Zhi, K. Nima, K. Faisal, and A. Paul, “Domino effect analysis of dust explosions using Bayesian networks,” Process Safety and Environmental Protection, vol. 100, pp. 108–116, 2016.

[7] L. David and N. F. Thornhill, “Process disturbance cause & effect analysis using Bayesian networks,” IFAC Papers Online, vol. 48, no. 21, pp. 1457–1464, 2015.

[8] K. Nima, “System safety assessment under epistemic uncertainty: using imprecise probabilities in Bayesian network,” Safety Science, vol. 116, pp. 149–160, 2019.

[9] O. C. Andrew and M. Ali, “A general cause based methodology for analysis of common cause and dependent failures in system risk and reliability assessments,” Reliability Engineering & System Safety, vol. 145, pp. 341–350, 2016.

[10] Z. Esmaili, A. Ali, K. Nima, and M. A. Mostafa, “Dynamic safety assessment of natural gas stations using Bayesian network,” Journal of Hazardous Materials, vol. 321, pp. 830–840, 2017.

[11] S. Marco, “Bayesian network models for incomplete and dynamic data,” Statistica Neerlandica, vol. 74, no. 3, pp. 397–419, 2020.

[12] Z. J. Mei and L. Jing, “Maritime accident risk estimation for sea lanes based on a dynamic Bayesian network,” Maritime Policy and Management, vol. 47, no. 5, pp. 649–664, 2020.

[13] K. Nima, L. Gabriele, and R. Genserik, “Application of dynamic Bayesian network to performance assessment of fire protection systems during domino effects,” Reliability Engineering & System Safety, vol. 167, pp. 232–247, 2017.

[14] K. Nima, R. Genserik, A. Rouzbeh, and K. Faisal, “Vulnerability analysis of process plants subject to domino effects,” Reliability Engineering & System Safety, vol. 154, pp. 127–136, 2016.

[15] X. Wu, H. Liu, L. Zhang, and M. J. Skibniewski, Q. Deng and J. Teng, “A dynamic Bayesian network based approach to safety decision support in tunnel construction,” Reliability Engineering & System Safety, vol. 134, pp. 157–168, 2015.

[16] S. Montani, L. Portinale, A. Bobbio, and D. Codetta-Raiteri, “Radyban: a tool for reliability analysis of dynamic fault trees through conversion into dynamic Bayesian networks,” Reliability Engineering & System Safety, vol. 93, no. 7, pp. 922–932, 2008.

[17] Y. J. Chang, X. F. Wu, C. S. Zhang, and G. M. Chen, “Dynamic Bayesian networks based approach for risk analysis of subsea wellhead fatigue failure during service life,” Reliability Engineering & System Safety, vol. 188, pp. 454–462, 2019.

[18] W. Deng, H. Liu, J. Xu, H. Zhao, and Y. Song, “An improved quantum-inspired differential evolution algorithm for deep belief network,” IEEE Transactions on Instrumentation and Measurement, vol. 69, no. 10, pp. 7319–7327, 2020.
[19] X. Wei and W. X. Zhou, “Integrated pipeline corrosion growth modeling and reliability analysis using dynamic Bayesian network and parameter learning technique,” Structure and Infrastructure Engineering, vol. 16, no. 8, pp. 1161–1176, 2020.

[20] K. P. Murphy, Dynamic Bayesian Networks: Representation, Inference and Learning, University of California, Berkeley, California, 2002.

[21] F. Donya, K. Nima, R. Genserik, and C. Valerio, “Security vulnerability assessment of gas pipelines using discrete-time Bayesian network,” Process Safety and Environmental Protection, vol. 111, pp. 714–725, 2017.

[22] J. Heng, K. Zheng, S. Kaewunruen, J. Zhu, and C. Baniotopoulos, “Dynamic Bayesian network-based system-level evaluation on fatigue reliability of orthotropic steel decks,” Engineering Failure Analysis, vol. 105, pp. 1212–1228, 2021.

[23] J. Liu and E. Zio, “System dynamic reliability assessment and failure prognostics,” Reliability Engineering & System Safety, vol. 160, pp. 21–36, 2017.

[24] E. Zio, Computational Methods for Reliability and Risk Analysis, Polytechnic of Milan, Italy, 2009.

[25] Y. J. Song, D. Q. Wu, W. Deng et al., “Multi-population parallel co-evolutionary differential evolution for parameter optimization,” Energy Conversion and Management, vol. 228, 2021.

[26] W. Deng, J. J. Xu, Y. J. Song, and H. M. Zhao, “Differential evolution algorithm with wavelet basis function and optimal mutation strategy for complex optimization problem,” Applied Soft Computing, vol. 100, pp. 1–16, 2021.

[27] Y. J. Song, D. Q. Wu, A. Wagdy, and X. B. Zhou, “Enhanced Success History Adaptive DE for Parameter Optimization of Photovoltaic Models,” Complexity, vol. 2021, Article ID 6660115, 22 pages, 2021.

[28] W. Deng and J. J. Xu, “An enhanced MSIQDE algorithm with novel multiple strategies for global optimization problems,” IEEE Transactions on Systems, Man, and Cybernetics: Systems, vol. 99, 2020.

[29] N. Khakzad, “Modeling wildfire spread in wildland-industrial interfaces using dynamic Bayesian network,” Reliability Engineering & System Safety, vol. 189, pp. 165–176, 2019.

[30] Z. K. Li, T. Wang, W. Ge, D. Wei, and H. Li, “Risk analysis of earth-rock dam breach based on dynamic bayesian network,” Water, vol. 11, no. 11, 2019.

[31] J. M. Craven, J. Switzenbank, V. N. Sharifi, and D. Peralta-Solorio, G. Kelsall and P. Sage, Development of a novel solids feed system for high pressure gasification,” Fuel Processing Technology, vol. 119, pp. 32–40, 2014.

[32] M. Hossein Sahraei, D. McCalder, R. Hughes, and L. A. Ricardet-Sandoval, “A survey on current advanced IGCC power plant technologies, sensors and control systems,” Fuel, vol. 137, pp. 245–259, 2014.

[33] F. Casella and P. Colonna, “Dynamic modeling of IGCC power plants,” Applied Thermal Engineering, vol. 35, pp. 91–111, 2012.

[34] D. J. Walker, “H-infinity control of gasification plant,” PROC INST MECH ENG I J SYST C, vol. 215, pp. 235–243, 2012.

[35] O. Shinada, A. Yamada, and Y. Koyama, “The development of advanced energy technologies in Japan,” Energy Conversion and Management, vol. 43, no. 9-12, pp. 1221–1233, 2002.

[36] J. Wang, H. Liu, Q. Liang, and J. Xu, “Experimental and numerical study on slag deposition and growth at the slag tap hole region of Shell gasifier,” Fuel Processing Technology, vol. 106, pp. 704–711, 2013.

[37] H. Zhou, T. Xie, and F. You, “On-line simulation and optimization of A commercial-scale shell entrained-flow gasifier using a novel dynamic reduced order model,” Energy, vol. 149, pp. 516–534, 2018.

[38] N. G. Guo, X. Xu, and W. T. Jiao, “Statistical analysis about zero-failure data with exponential distribution,” Journal of Light Industry, vol. 5, pp. 117–120, 2008, (in Chinese).

[39] R. A. Waller and H. F. Martz, “A bayesian zero-failure (BAZE) reliability demonstration testing procedure,” Journal of Quality Technology, vol. 11, no. 3, pp. 128–138, 1979.

[40] P. Jiang, Y. Xing, X. Jia, and B. Guo, “Weibull failure probability estimation based on zero-failure data,” Mathematical Problems in Engineering, vol. 2015, Article ID 681232, 8 pages, 2015.

[41] H. D. Nguyen and E. Gouno, “Maximum likelihood and Bayesian inference for common-cause of failure model,” Reliability Engineering & System Safety, vol. 182, pp. 56–62, 2019.

[42] N. Fang, Z. Li, J. Wang et al., “Experimental investigations on air/particle flow characteristics in a 2000 t/d GSP pulverized coal gasifier with an improved burner,” Energy, vol. 165, pp. 432–441, 2018.

[43] R. Jurgeleitena and P. J. F. Lucas, “Exploiting causal independence in large Bayesian networks,” Knowledge-Based Systems, vol. 18, no. 3, pp. 153–162, 2004.