Design of a Wireless Sensor Network-Based Risk Assessment Algorithm for Cave Collapse

Xiaoyang Pei

Yulin University, College of Art, Yulin, Shaanxi Province 719000, China

Correspondence should be addressed to Xiaoyang Pei; peixiaoyang@yulinu.edu.cn

Received 28 March 2022; Revised 17 April 2022; Accepted 28 April 2022; Published 31 May 2022

Academic Editor: Abid Yahya

Copyright © 2022 Xiaoyang Pei. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Accidents frequently happen during tunnel and subway construction. This study defines the cave collapse types based on the investigation results of a cave collapse in Yanchang County, the precise scenario of the cave collapse, paired with Yan’an City. Flac3D software is used to simulate the slope before and after the excavation of the cave. The findings of comparing the stress and strain characteristics of the soil slope lead to the cave’s destruction. A comprehensive risk probability estimation method based on interval probability level of accident tree and Bayesian network, weight confidence index, and confidence interval is proposed to solve the problems of subjectivity and inaccurate results in tunnel risk assessment, and it is applied to the risk assessment of cave collapse. First, the Bayesian network was constructed by using accident tree, and the conditional probability (joint probability) of sensor nodes is obtained by using the dependence relationship between the case factors. Then, the pij estimated value of expert J for the occurrence probability of the fundamental event Xi was calculated using the interval probability grade division and weight confidence index approach. The sample space U and its statistics were constructed from the estimated values of all experts, and the probability range of the occurrence probability of the basic event Xi was obtained by introducing the confidence interval method. For risk inference, the probability range of all occurrences is derived and integrated with the conditional probability of a Bayesian network, ensuring the scientific correctness and precision of risk assessment. At the same time, the model can be used to determine the cause of an accident. According to our experimental results, cave collapse causes were investigated soon after an accident occurred, allowing for the development of risk management strategies to prevent future occurrences.

1. Introduction

According to the report of China Engineering technology Development Research held in 2020, the underground engineering such as subway is a complex system engineering with high risk. The development and utilization of underground space in the controlled country is listed as an important subject [1]. Inadequate tunnel and construction will cause significant property losses, casualties, construction delays, and adverse social impacts. Totally, 199 accidents that happened during tunnel and subway construction from 2001 to 2016 were statistically examined after accident records were collected from the Ministry of Housing and Urban-Rural Development, the State Administration of Work Safety, and other relevant departments. These accidents were divided into 9 categories, including collapse accident (such as collapse, ground subsidence, and roof falling accident), fire and explosion accident, harmful gas suffocating accident, and mechanical accident. The number of accidents caused by collapse accounts for more than half of the all accidents [2]. As a result, for the purpose of identifying accident risk factors and estimating risk probability, this study chooses the collapse accident.

In order to avoid accidents, a large number of studies have been carried out for risk identification and evaluation methods on both national and international levels, which were divided into qualitative evaluation, semi-quantitative evaluation, and quantitative evaluation [3]. The main methods include Delphi method [4], accident tree method [5], Monte Carlo method [6], ANALYTIC Hierarchy Process [7], network analysis [8], fuzzy analytic hierarchy process [9], fuzzy network analysis [10], extension method [11], Bayesian network method, etc. The application of the above methods plays an important role in improving the
ability of risk prediction and reducing the occurrence of accidents. The accident tree approach can investigate the reason of an accident in depth; however, it is very subjective, and it cannot be computed when data are unavailable. Bayesian network can use expert experience or existing cases as prior knowledge, which can improve the accuracy of prediction when data are incomplete, but it requires prior knowledge.

Loess cave dwelling is a characteristic type of dwelling house in Loess Plateau of China, which is the product of plateau geology, landform, history, and culture. Cave collapse is a geological disaster caused by artificial kiln construction, which is common in Yanchang County. According to the investigation, there are hundreds of incidents of slope instability in Yanchang County caused by cave demolition, which is the major cause of catastrophic deaths. For this study, first, the data of use cases are used as prior knowledge to construct a Bayesian network and the conditional probability of nodes is calculated. Next, a confidence interval probability level and weight index method are proposed. After that the confidence interval is estimated, and the probability of the comprehensive risk evaluation method is evaluated. Finally, the project is implemented in the Yuliang Tunnel, China, which enhances the accuracy of risk factor identification and evaluation, increases risk management, and minimizes possible engineering risk, and may serve as a model for future risk assessment of similar projects.

The investigation revealed the destruction of cave dwellings in Yanchang County is divided into three types:

1. Local collapse failure, in which the soil near the cave dwellings falls or collapses along the soft structural plane under the action of dead weight, and the soil becomes unstable and collapses due to the action of joints in the loess.

2. Refers to the overall collapse or collapse of the cave’s soil, thus destroying the structure and integrity of the soil, causing slope collapse.

3. Water seepage and cracks in the cave. The stress distribution in the cave is affected by natural or manmade factors, resulting in massive cracking of the soil layer and mud layer, which destroys the structure of the soil slope and causes collapse, or water seepage in the cave, causes destruction of the loess structure and overall soil slope collapse.

The excavation of cave can affect the stress distribution of soil slope and produces stress concentration on the surface of cave, thus changing the original stress and strain characteristics of soil slope is an important reason leading to the destruction of cave. In order to discuss the stress, strain, and failure process of the cave, taking the collapse of Gaoxiuying house in Xialuopi, Yanchang County as an example. Flac3D software was used to simulate the soil slope before and after the excavation of the cave. While the stress, strain, and deformation in the soil slope were analyzed, and failure mechanism of the cave collapse was further discussed. According to the understanding of the collapse on-site and the principle of finite difference method, a model of the collapse of Luo PI Gao Xiuying’s house can be established (Figure 1). The collapse of material is given emphasis with field surveying, measuring, and recording in order to replicate the 3-dimensional model. Model range for 88 m broad (x direction), front of high slope 14 m (z direction), rear of 34 m high, depth for 66 m (y direction), and two unloading fissures and one unloading cranny on cave walls as weak structural plane. The model’s border is considered as a fixed, constrained element, and no lateral or vertical displacements occur throughout the computation process. The rest are treated as free boundaries. In addition to selecting parameters based on the results of the experimental test, the analogy approach might very well be used to pick parameters.

The rest of this paper is organized as follows. In Section 2, the related work about the proposed algorithm is presented. In Section 3, risk probability calculation method based on accident tree and Bayesian network are discussed. In Section 4, the experimental results are discussed. Finally, this paper is concluded in Section 5.

2. Related Work

Cave excavation slope stress state analysis of cave before excavation of the slope stress state analysis of numerical simulation that is in front of the cave excavation slope in gravity stress field simulation can understand this kind of slope influence on stress field [12]. Caves before and after excavation of gravity stress field simulation can be compared. It can be seen from the figure that the maximum principal stress of the stress field formed under gravity is approximately parallel to the slope surface and gradually turns to water level after it is away from the slope surface [13]. In addition, the maximum principal stress increases with the increase of y direction, and its value reaches to 0.6 MPa. The stress concentration occurs at the vertical scarp in front of the slope, and the maximum value reaches 0.2 MPa [14]. Under the influence of other factors, the scarp in front of the slope will be deformed and destroyed. The maximum displacement of the slope under the action of deadweight is close to 2.5 mm, which conforms to the displacement distribution rule under the general deadweight stress.
There are many methods and means for cave collapse monitoring around the globe. These methods are roughly divided into different categories. These categories include cable and wireless technologies, attributed to the complicated cave collapse area’s geological characteristics, line construction difficulties and power supply limit. It is difficult to establish a cable system, system maintenance is cumbersome, and the monitoring network structure’s dependability is low; many of them are basic sensor monitoring nodes linked together, and when a sensor node fails, the monitoring network structure fails [15, 16]. The normal operation of the following nodes will be affected, thus affecting the effectiveness of the whole system. In addition, the information monitored by many monitoring systems is limited, which cannot provide sufficient data support for correct, timely forecast and early warning, thus affecting the reliability of system. Existing wireless monitoring methods, such as Global Positioning System (GPS) and Geographic Information System (GIS) [17], have high equipment costs. Interferometric Synthetic Aperture Radar (InSAR) has the characteristics of all-weather, continuous information acquisition and high spatial resolution, but this method has high requirements on the quality of interferometric phase images, requiring high-resolution satellite remote sensing images. Therefore, it is determined that these methods are not suitable for large-scale promotion and application.

Wireless Sensor Networks (WSN) is an emerging network information acquisition and processing technology, which has the functions of Ad hoc network, wireless multihop routing, and multipath data transmission [18]. Combined with data fusion technology, WSN can balance network load and prolong network life cycle [1]. The cost of sensor nodes is low, which can realize a wide range of node layout for the whole landslide monitoring area and ensure the depth of data acquisition.

Cave collapse monitoring system consists of wireless sensor monitoring network, General Packet Radio Services (GPRS) gateway, and remote monitoring center. In order to obtain real-time and effective information of the monitoring area, a large number of sensor nodes are placed in the monitoring area to measure the displacement and acceleration values of cave dwellings [19]. Since landslides are mainly generated by groundwater erosion, the depth of underground water level is an important indicator to show the collapse risk of cave dwellings. The liquid level depth sensor deployed at the bottom of the hole and sent by wireless network collects the liquid level. Mountain is often composed of multiple layers of soil or rock, different levels due to physical composition and erosion of different degrees, and its movement speed is different [20]. The occurrence of this phenomenon, deployed in different depths of the tilt sensor will return different tilt data, through the tilt sensor can monitor the movement of the mountain. In the measurement process, the sensor node automatically adjusts the information collection frequency and the amount of information collection, while the coordinator and router node construct the information transmission network and its routing based on flood plain routing. The terminal router node of the network is taken as the cluster head, the cluster network is established with the sensor node, and the collected information is transmitted and aggregated. The cluster-head node performs de-redundancy processing on the information and sends it to the coordinator connected with GPRS gateway through plain routing. GPRS gateway sends the aggregated information to the remote monitoring center in a customized data format. The remote monitoring center will process the received information to realize the accurate early warning and forecast of cave collapse.

3. Risk Probability Calculation Method Based on Accident Tree (FAT) and Bayesian Network (NB)

It is assumed that \( x_i \) and \( T \) represents the variables of the basic event and overhead event, 0 and 1 states represent the occurrence and nonoccurrence of the event, respectively. The top event \( T \) will be determined by the state of the basic event in accident tree. When the top event \( T \) occurs (\( T = 1 \)), the corresponding state of the base event is \( T = 1 \). When 0 and 1 are taken, the probability calculation formulas of AND gate and OR gate are shown in (1) and (2), respectively, where \( P(x_i = 1) \) represents the probability of occurrence of the basic event \( x_i \).

\[
P_{\text{and}} = \prod_{i=1}^{n} P(x_i = 1),
\]

\[
P_{\text{or}} = 1 - \prod_{i=1}^{n} P(x_i = 1).
\]

\( T \) is a set of directed edges, indicating the dependence or causality between related variables (the parent node points to the child node, the root node is the one without the parent node, while the leaf node is the one without the child node). It is suitable for the description and analysis of uncertain probabilistic events that can be applied to the conditional decision depends on multiple influencing factors, which can make reasonable inference under the condition of incomplete and uncertain information. The Bayesian network represents the relationship between the parent node \( T(x_i) \) and the child node \( x_i \) and also confirms that the child node is independent from other unrelated node \( A(x_i) \), as shown in (3).

\[
P(x_i | \pi(x_i), A(x_i)) = P(x_i | \pi(x_i)).
\]

As a Bayesian network, the node one-to-one connection and logic relations are preserved through fault tree building. It uses accident scenarios in the root node and intermediate nodes while leaf nodes appear as dependencies. Because each fundamental event conditional independence between the joint probability formulas may be reduced by winding in previous information, all the nodes of conditional probability can be obtained. (4) can be used to calculate the probability of a leaf node in a Bayesian network.

\[
P(X) = P(x_1, x_2, \ldots, x_n),
\]

\[
= \prod_{i=1}^{n} P(x_i | \pi(x_i)) .
\]
method, and the conditional probability obtained by case
prior knowledge can be obtained by (5), where, \( n \) represents
the number of root nodes, each root node \( x_i \) can take two
state parameters 0 and 1, respectively, so \( n \) nodes will have \( 2^n \)
combinations.

\[
P(T = 1) = \sum_{i=1}^{2^n} [P(T = 1|x_1, x_2, \ldots, x_n) \times P(x_1, x_2, \ldots, x_n)].
\]  

(5)

In this paper, trigonometric fuzzy function is selected to
represent the membership probability of nodes of Bayesian
network, and its function \( U = (a, m, b) \) is shown in (6). \( a \) and
\( b \) represent the lower limit and upper limit of fuzzy number,
respectively, while \( m \) represents the mean value. Assuming
that there are two triangular fuzzy numbers, which are
divided into \( U_1 = (a_1, m_1, b_1) \) and \( U_2 = (a_2, m_2, b_2) \), the four
algorithms are shown in (7).

\[
U_1 + U_2 = (a_1 + a_2, m_1 + m_2, b_1 + b_2),
U_1 - U_2 = (a_1 - a_2, m_1 - m_2, b_1 - b_2),
U_1 \times U_2 = (a_1 \times a_2, m_1 \times m_2, b_1 \times b_2),
U_1 + U_2 = (a_1 + a_2, m_1 + m_2, b_1 + b_2).
\]  

(7)

According to the curve form of normal distribution, the
probability of event occurrence will gradually decrease on
both sides of the probability interval selected by experts, and
the closer gets to the selected interval, while the probability
will be greater. The probability of falling into the probability
interval 1 is determined by (8)

\[
P_I = \begin{cases} 
0, & x \leq m, \\
\frac{x - a}{m - a}, & a \leq x \leq m, \\
\frac{b - x}{b - m}, & m \leq x \leq b, \\
0, & x \geq b,
\end{cases}
\]  

(6)

\[
P_{i1} = \begin{cases} 
\frac{a_k - a_{k-1}}{\sum_{l=1}^{k-1} a_k - a_{k-1}} \times 1 - \frac{\theta}{2}, & 1 \leq l \leq k - 1, \\
\theta, & l = k, \\
\frac{a_{l+1} - k}{\sum_{l=1}^{k-1} a_k - a_{k-1}} \times 1 - \frac{\theta}{2}, & k + 1 \leq l \leq 9.
\end{cases}
\]  

(8)

Expert \( J \) uses (9) to process the estimated probability
result of the occurrence of basic event XI, and it can be
concluded that multiple experts (assuming \( n \)) in practical
engineering application will investigate the estimated probability
value of its occurrence, while the evaluation result given by each expert will be processed by functions 9 and 10. Each expert’s estimate of the probability of occurrence of the base event (observed value) is obtained. Since

the variance of the sample population is unknown, the
sample variance \( S \) is selected instead in (11).

\[
P_{ij} = E(p_i) = \sum_{j=1}^{n} m_i \times P_{ij},
\]  

(9)

\[
S^2 = \sum_{j=1}^{n} (P_{ij} - P_i)^2 / n - 1,
\]  

(10)

\[
P_i = \sum_{j=1}^{n} P_{ij} / n,
\]  

(11)

\[
T_i = \frac{P_i - \mu_i}{\sqrt{S^2/n}} \sim t(n - 1).
\]  

(12)

Then, for a given \( a \), let

\[
P \left( \frac{P_i - \mu_i}{\sqrt{S^2/n}} \leq t_{(a/2)}(n - 1) \right) = 1 - a.
\]  

(13)

Look up the table for the distribution of \( t \), and you get the
value of \( t(n - 1) \).

\[
P \left( P_i - \frac{S_i}{\sqrt{n}} t_{(a/2)}(n - 1) \leq \mu_i \leq P_i + \frac{S_i}{\sqrt{n}} t_{(a/2)}(n - 1) \right) = 1 - a.
\]  

(14)

Then \( u \) is located in the confidence interval of \( 1 - a \):

\[
\left[ P_i - \frac{S_i}{\sqrt{n}} t_{(a/2)}(n - 1) \leq \mu_i \leq P_i + \frac{S_i}{\sqrt{n}} t_{(a/2)}(n - 1) \right].
\]  

(15)

The probability trigonometric fuzziness of the fundamental
event can be obtained by the investigation method and the
confidence interval method.

4. Experimental Results and Analysis

It can be seen from Figure 2 that the maximum principal
stress at the top and around the sidewall of the cave is
basically parallel to it. Due to the constraints of other
mountains on the bottom of the mountain on its shape in X,
Y, and Z direction, the force is between 0.06 MPa and
0.16 MPa. The principal stress on the wall and bottom of the
cave is close to 0. It can be seen from Figure 3 that after the
evacuation of the cave, the displacement around the cave has
changed significantly, and it gradually increases from a
distance to the cave wall with a normal circumference of
0.05 mm to 0.2 mm. Under the influence of other factors, it is
easy to drop blocks on the top wall of the cave, and the
displacement rebound phenomenon occurs at the bottom of
the cave with a value of 0.15573 mm.

When the system starts, the computer terminal sends a
command to sink node requesting node location, and the
node measures the distances \( d1, d2, \) and \( d3 \) to the three
beacon nodes using its own positioning function module.
and sends it back to the computer terminal, which calculates the unknown node’s coordinates and displays them on the system interface. If a computer terminal needs to know if a node is dead, for the node to start detecting faults, it has to send a fault monitoring command. When the detection is complete, the computer terminal sends back the detection result, which is then displayed on the system interface by the computer terminal. Figure 4 depicts the system’s main user interface.

According to the fundamental incident, the accident tree approach was used to design the accident risk factors, which were then used to construct the questionnaire and expert inquiry. A total of 25 professionals are involved in the inquiry, each of whom conducts an effective survey. Table 1 shows 20 copies of the weight of fundamental events X₀ and confidence, with a weight distribution of 1, 0.9, 0.8, 0.7, 0.6 and experts having 3, 3, 6, 5, 3 copies. The experts use (9) to calculate the probability grade distribution rule of the occurrence, while (10) is used to process the evaluation results of the experts to obtain the respective estimated values of the four experts.

The influence factors of tunnel collapse are complicated, and most accidents are the result of the interactions by many factors. Through the analysis of 47 collapse accidents, the tunnel being in the limit state as well as not being detected and treated in time causes the collapse. In this paper, the influence factors and probability estimation that lead to the tunnel being in the limit state are not considered for the time being. Through the statistical analysis of accident cases, the basic events and intermediate events are obtained. After a detailed analysis of the cause of the accident, the cause analysis or investigation report of the statistical collapse accident was used to construct the collapse accident tree, as shown in Figure 5.

If the conditional probability table is derived from the data, the fuzzy probability value of the occurrence of each basic event obtained by experts after data processing is the probability of collapse accident at the entrance section of Yuliao tunnel is 5.321 percent, 7.66 percent, and 10.02 percent, respectively, indicating that the level of risk probability is N. Because a tunnel collapse accident is possible, we must pay close attention to this task in safety management.

![Figure 2: Cloud diagram of slope maximum principal stress distribution.](image1)

![Figure 3: Displacement cloud map in z direction after cave excavation.](image2)

![Figure 4: Main interface of the system.](image3)

![Table 1: Survey table of occurrence probability of basic event X₀.](image4)
The list of tunnel risks should not only be sorted out before the tunnel construction but also simulation analysis should be carried out for the specific situation in the construction process of tunnel construction. As a result, the risk of tunnel construction collapse is more accurate. For example, in the construction process of F tunnel, the strength of surrounding rock of F tunnel is V grade, which means that in the process of tunnel construction, if the designer does not carry out reasonable planning in the process of planning, it is likely to cause landslide. In the process of tunnel building simulation analysis, the first need is for the "Highway tunnel design code" to be used for the calculation of stability coefficients using the predicted value specified in the code. Moreover, the stress calculation of the structure is carried out for the condition of unsealed front and back according to the specific data (as shown in Table 2).

The stress calculation results can be used to calculate the support stability coefficient at the initial stage of tunnel construction, and corresponding measures can be taken to solve specific problems in the process of tunnel construction. After the temporary support is removed, the secondary lining correction and monitoring should be completed as quickly as possible. For example, in the process of digging the center surrounding rock, the initial support should be completed on time. It is required to conduct out blasting management, optimize the placement of the hole, the quality of explosives, and other parameters in the process of rock blasting to the maximum degree possible to minimize undue disruption to the surrounding rock. In this way, the risk assessment of tunnel construction collapse can not only play the role of assessment but also reduce the risk of collapse in the process of tunnel construction.

By using the inference ability of Bayesian network, the cause of collapse accident is analyzed and diagnosed. A Bayesian network based on its prior knowledge and the known circumstances may derive the probability of each component contributing to the occurrence of the accident or probability of certain fundamental occurrences after the occurrence of tunnel collapse is set as an evidence variable. If a tunnel collapses, the various reasons of the collapse may be studied in real time, as illustrated in Figure 6, so that the causes can be evaluated in real time after an accident happens and risk mitigation measures can be proposed to prevent such disasters.

The estimation method of risk probability combining accident tree and Bayesian network is applied to accident analysis of tunnel collapse for the first time. After collecting 47 collapse cases, 16 basic events and 5 intermediate events leading to collapse accidents are determined by using the accident tree method, and the dependence relationship between each event is established, so as to construct the Bayesian network and obtain the conditional probability of nodes. The method makes full use of the analysis ability of accident tree and reasoning ability of Bayesian network in case of uncertainty or incomplete conditions. It also estimates the risk probability of the entrance section of cave kiln, analyzes and studies the influence importance degree of its basic events, and determines the key points of prevention in this project.

By analyzing the survey data in the statistical table, we can get the grade of excavation width and the frequency of different grades of collapse, and then we can use the fuzzy statistical method to get the membership degree matrices respectively, as shown in Figure 7.

| Working condition | Load sharing ratio (%) | Bending moment (kN/m) | Axial force (kN) | Axial force (kN) |
|-------------------|------------------------|----------------------|-----------------|-----------------|
| 1                 | 30                     | 110.5                | 1130.5          | 2.28            |
| 2                 | 100                    | 353.5                | 3664.9          | 0.72            |
| 3                 | 15                     | 119.8                | 492             | 1.21            |
| 4                 | 30                     | 227.5                | 949.2           | 0.64            |
| 5                 | 30                     | 201.2                | 1051.5          | 0.85            |
| 6                 | 30                     | 113                  | 1115            | 2.22            |

Table 2: Local stress calculation results.

![Bayesian network for cave collapse.](image-url)
5. Conclusion

This study observed that before the cave excavation, the stress in the slope soil is in a natural equilibrium, and the weakness has no impact on the slope. However, the existence of soft surface leads to the displacement and deformation of the cave wall, which destroys the integrity and stability of soil structure around the cave. Therefore, the excavation of cave dwellings often leads to the change of slope stress: from local stress concentration to soil deformation and destruction, which leads to the destruction of cave dwellings. The application of Wireless Sensor Network (WSN), the latest innovation in the field of Information Technology, has advantages as compared to traditional technology to cave collapse monitoring. This paper presents a design scheme of real-time monitoring and early warning system for cave collapse based on WSN technology.
The system architecture and each important component of the proposed system are introduced in detail, including hardware component and software design. Flood routing, mesh network structure, cluster network structure, and on-demand sampling technology are used in the area of environmental information real-time sampling and real-time transmission to lose, decrease data sampling system, and elevate cave collapse, among other things. Because of the high dependability of natural catastrophe monitoring and real-time prediction warning, the sensor node installation flexibility has been increased. At the same time, the GPRS gateway sends the collected environmental monitoring information to realize the remote monitoring of the environment to be monitored, which improves the remote monitoring ability of environmental monitoring, the application value, and scope of the whole system.

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

Conflicts of Interest
The author declares that he has no conflicts of interest.

Acknowledgments
This paper was supported by one of the phased achievements of the 2017 Ministry of Education (project number: 17YJC760061) and the Research on Building Technology Development and Application Technology of Northern Shaanxi Cave Manor (project number: 2019-90-5) of Yulin Science and Technology Bureau in 2019.

References
[1] G. Antonello, N. Casagli, P. Farina et al., “A Ground-Based Interferometer for the Safety Monitoring of Landslides and Structural Deformations,” in Proceedings of the International Geoscience and Remote Sensing Symposium, pp. 218–220, IEEE, Toulouse, France, May 2003.
[2] P. Mehta, D. Chander, M. Shahim, K. Tejaswi, S. N. Merchant, and U. B Desai, “Distributed Detection for Landslide Prediction Using Wireless Sensor Network,” in Proceedings of the First International on Global Information Infrastructure Symposium, pp. 195–198, Marrakech, Morocco, December 2007.
[3] R. Ohbayashi, Y. Nakajima, H. Nishikado, and S. Takayama, “Monitoring System for Landslide Disaster by Wireless Sensing Node Network,” in Proceedings of the SICE Annual Conference, pp. 1704–1710, IEEE, Chofu Japan, October 2008.
[4] B. Li, S. Li, L. Chen, X. Li, and S. Qu, “Design and Realization of Wireless Remote Image Monitoring System Based on GSM/GPRS,” in Proceedings of the Third International Forum on Strategic Technologies, pp. 260–263, IEEE, Novosibirsk Russia, August 2008.
[5] T. Pei, F. Lei, Z. Li et al., “A d-aware congestion control protocol for wireless sensor networks,” Chinese Journal of Electronics, vol. 26, no. 3, pp. 591–599, 2017.
[6] H. Y Wang and J. Y. Wang, “Design and implementation of a smart home based WSN and AMR,” Applied Mechanics and Materials, vol. 2181, no. 271, pp. 1485–1489, 2013.
[7] C. J. Qi and H. W. Wang, “The wireless sensor system based on the chip of STM32 and SH79F32,” Applied Mechanics and Materials, vol. 548-549, no. 548, pp. 744–747, 2014.
[8] X. R. Jiang, Y. M. Lv, and X. H. Cheng, “Design of wireless communication system based on nRF24L01,” Advanced Materials Research, vol. 945-949, no. 945, pp. 1756–1759, 2014.
[9] T. Zhang, “Research and application of serial communication modules based on VB,” Energy Procedia, vol. 11, pp. 2033–2037, 2011.
[10] Y. Y. Xu and Y. Wang, “Design of temperature monitoring system of laboratory based on VB,” Advanced Materials Research, vol. 926-930, no. 926, pp. 1297–1300, 2014.
[11] P. Larson, C. Clinciu, and E. Hanson, “SQL Server Column Store Indexes,” in Proceedings of the ACM SIGMOD International Conference on Management of Data, pp. 1177–1184, Athens, Greece, June 2011.
[12] J. Zhao and Q. Luo, “Medical Research Based on SQL Server Database,” in Proceedings of the 2012 International Conference on Cybernetics and Informatics, pp. 727–733, Springer, New York, NY, April 2014.
[13] L. B. Ruiz, I. G. Siqueria, H. C. Wong, L. B. E. Oliveira, J. M. S. Nogueira, and A. A. F Loureiro, “Fault management in even-driven wireless sensor network,” in Proceedings of the 7th ACM international symposium on modeling, analysis and simulation of wireless and mobile systems, pp. 149–156, ACM, New York, NY, U S A, October 2004.
[14] A. Woo, T. Tong, and D. Culler, “Taming the underlying challenges of reliable multihop routing in sensor network,” in Proceedings of the 1st international conference on embedded network sensor systems, pp. 14–27, ACM, New York, NY, U S A, November 2003.
[15] J. Chen, S. Kher, and A. Somani, “Distributed fault detection of wireless sensor networks,” in Proceedings of the 2006 workshop on dependability issues in wireless ad hoc networks and sensor networks, pp. 65–72, ACM, New York, NY, U S A, September 2006.
[16] H. H. Einstein and S. G. Vick, “Geological model for tunnel costmodel,” in Proceedings of the Procapid Excavation and Tunneling Conf, 2nd, pp. 1701–1720, San Francisco, California, June 1974.
[17] H. H. Einstein, “Risk and risk analysis in rock engineering,” Tunnelling and Underground Space Technology, vol. 11, no. 2, pp. 141–155, 1996.
[18] H. H. Einstein, S. Xu, P Grasso, and M. A. Mahtab, “Decision Aids in Tunneling,” Word Tunneling April, pp. 157–159, 1998.
[19] B. Nilsen, A. Palmstrom, and H. Stille, “Qualitye Ontrol of a Subsea Tunnel Project in Complex Ground conditions,” Challenges for the 21 Stentury, vol. 44, pp. 137–145, 1992.
[20] R. Sturk, L. Olsson, and J. Johansson, “Risk and decision analysis for large underground projects, as applied to the Stockholm Ring Road tunnels,” Tunnelling and Underground Space Technology, vol. 11, no. 2, pp. 157–164, 1996.