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Pre-Alarm System Based on Real-Time Monitoring and Numerical Simulation Using Internet of Things and Cloud Computing for Tailings Dam in Mines

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ABSTRACT The tailings dam, a necessary facility to maintain the normal operation of mining enterprises, is a hazard source of human-caused debris flow with high potential energy. The real-time pre-alarm for the instability of tailings dam is vital to ensure the normal mining and safety of human lives and properties. Based on the Internet of Things and wireless networks, the multiple and the key information system of tailings dam is constructed using the sensor data, which include the stability indexes like phreatic line, reservoir water level, internal and external deformation of the tailings dam. The cloud platform is applied to predict the future state of the phreatic line based on real-time monitoring data, where the equation of phreatic line can be obtained. The numerical simulation model is established by considering the predicted equation of phreatic line, limit equilibrium state parameters, reservoir water level, and rainfall. Then, the safety factor, random reliability, and interval non-probabilistic reliability can be solved out through the cloud platform. Combined with the trend of real-time monitoring deformation, as well as calculated dynamic safety factor, random reliability, and interval non-probabilistic reliability, the stable or dangerous warning signals of tailings dam can be obtained by the remote real-time pre-alarm system. The main solved method for the key parameters and pre-alarm process are presented through a case study. It is proved that the pre-alarm system is an efficient and real-time platform for the tailings dam stability with the integration and mutual validation of key information.

INDEX TERMS Cloud computing, Internet of Things, interval non-probabilistic reliability, pre-alarm system, tailings dam.

I. INTRODUCTION

The tailings dam is a necessary facility to maintain the normal operation of mining enterprises, but it is a hazard source of man-made debris flow with high potential energy. Its stability and security are vital to the normal production of mining enterprises and the regional ecological security [1]–[3]. Therefore, it is very important to investigate the early warning of the tailings dam failure.

Some useful early warning and monitoring methods were developed to analyze or monitor the conditions of tailings dam. Li *et al.* [4] presented a new prediction method for phreatic line based on the support vector regression and the monitoring data of tailings dam. Yuan *et al.* [5] proposed a mathematical model of tailings dam failure according to some practical data of broken tailings dams. Wang [6] applied the grey theory and support vector machine to the prediction of tailings dam displacement and phreatic line based on the monitoring results of tailings dam displacement and phreatic line, which provided a new method for the stability analysis and reliability prediction of tailings dam. Jiang and Tang [7] and Tang *et al.* [8] proposed a general approximate method for the groundwater response problem caused by water level variation, and they also investigated the approximate analytical solution to the Boussinesq equation with a sloping water-land boundary, which can be used to determine the phreatic line under different water levels in tailings dam under the conditions without the measured data of observation holes. Blight [9] studied the dam failure of 5 ring tailings dams in South Africa. It was concluded that the transport distance of tailings flow was related to the dry and wet state of the ground surface, and the tailings flow in the wet surface was longer than that in the dry surface. Moxon [10] discussed the accident of tailings dam of Los Frailes mine in southern Spain, and proposed the measures to prevent dam failure. Rico *et al.* [11] established the relationship between the geometric parameters of tailings dam (dam height, storage etc.) and the fluid characteristics induced by tailings dam failure, based on the effective information of collected and summarized historical accidents of tailings dam. It provides an important guidance to analyze the relation between the disaster evaluation and parameters of tailings dam failure. Wei *et al.* [12] determined the monitoring parameters of tailings dam, including reservoir water level, dam displacement, phreatic line and dam video, to analyze the principle of tailings dam failure thoroughly. They also developed the safety monitoring and warning system for tailings dam. Li [13] monitored the tailings dam subsidence with high-precision EDM trigonometric leveling, established the model of subsidence monitoring data, and discussed the law of subsidence to predict the change trend of subsidence.

For the works of stability evaluation, the currently used safety factor method [14] and random reliability method [15] are not effective to solve the problem of real-time stability for tailings dam. The reason is that the safety factor method cannot consider the randomness of parameters. Although the random reliability method takes the randomness of the parameters into consideration, the coefficient of variation is often assumed or obtained by simple calculation without taking into account the time correlation, due to the huge workload and high cost of the repeated trial in the actual project. The interval non-probabilistic reliability analysis methods for structures [16]–[22] based on interval theory provide a useful approach to evaluate these uncertainties. Interval values can reflect the uncertainty of a parameter value better when the number of samples is scarce, thus reducing the demand for data information. Dong *et al.* [23], [24] developed interval non-probabilistic reliability for tailings dam and jointed surrounding rockmass. In this paper, the safety factor, random reliability, and interval non-probabilistic reliability are used to evaluate the tailings dam stability comprehensively.

However, it can be clearly found that existent manual or automatic intelligent monitoring methods are based on the already produced macro deformation, stress and water level of dam. They do not have the functions to evaluate the stability conditions, where the future trend is predicted with the monitored information.

In view of this, we use multiple information to establish a pre-alarm system of tailings dam in this paper. After analyzing monitoring data and predicting the development trend, the numerical simulation is used to evaluate the future situations of tailings dam, which plays an important role in early warning and control for the potential risk of tailings dam. In recent years, the Internet of Things (IOT) [25], cloud computing (CC) [26], wireless sensor networks [27]–[29], artificial intelligence [30]–[32], and numerical simulation technologies have provided a good technical guarantee for the achievement of this goal.

Therefore, the wireless network system for tailings dam with multi information is constructed by using the sensor to detect the phreatic line, water level of the monitoring hole, internal and external deformation, and the reservoir water level, which affect the stability of the tailings dam. In the cloud platform, firstly, the future state of the phreatic line is predicted based on the real-time monitoring data using artificial intelligence method. Secondly, the phreatic line equations are taken into the numerical model to solve out key stability parameters, which include the safety factor, random reliability and interval non-probabilistic reliability. In the application system, combined with key stability parameters and the trend of real-time monitoring deformation, as well as the crack propagation, the disasters of the tailings dam situation can be remotely and early alarmed.

II. THE HIERARCHICAL STRUCTURE OF PSRMNS-IOTCC

It is common that the conventional detection and monitoring system are used to calculate the operation parameters and evaluate the safety level of the tailings dam. However, some serious problems including the incompleteness of the traditional detection and monitoring system, the backwardness of the detection and monitoring technology, and the lack of the professional technical persons cause the great safety hazards for numerous tailings dams in the worldwide. Although the measurements will be performed regularly by technical persons using the traditional instruments, there is no doubt that the systematic error and manual operation error are inevitable due to the effects of weather, personal technique and experience, as well as the site conditions, which will affect the safety management level of the tailings dam. Therefore, it is necessary to develop and achieve the automatic and real-time monitoring for various parameters and indexes of the tailings dam based on the modern communication technology and equipment, as well as the computer technology.

In view of the above-mentioned facts, the pre-alarm system based on real-time monitoring and numerical simulation using Internet of Things and cloud computing for tailings dam in mines (PSRMNS-IOTCC), which is integrated through the IOT and the CC, were developed to comprehensively monitor the safety situations and pre-alarm the possible hazards of the tailings dam. Firstly, through multiple types of wireless sensors laid at the specific places of the tailings dam, the corresponding data can be received and uploaded to the cloud computing platform through the internet. Then, they will be processed by the cloud computing

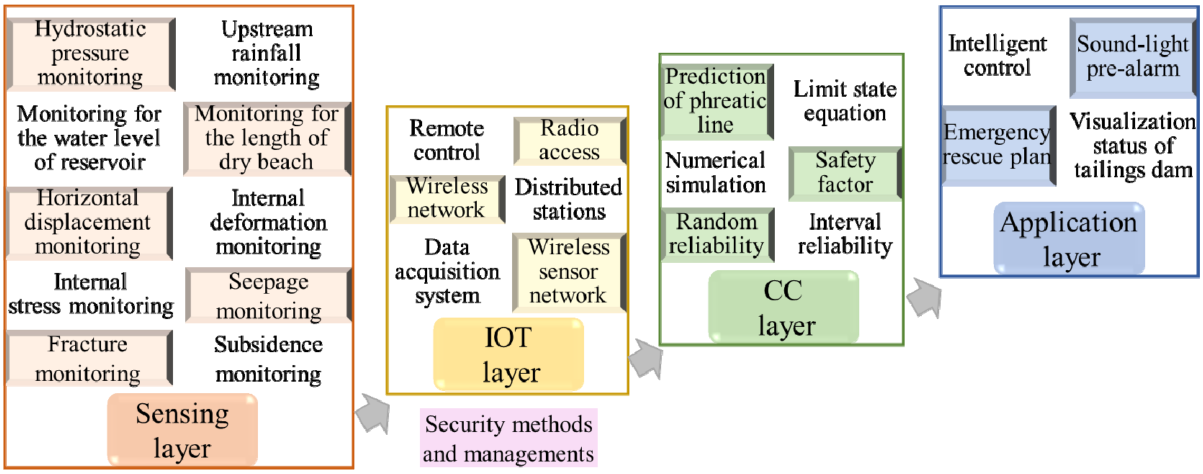

FIGURE 1. The hierarchical structure of PSRMNS-IOTCC for the tailings dam. The framework consists of four layers, which are the sensing layer, IOT layer, CC layer, and application layer.

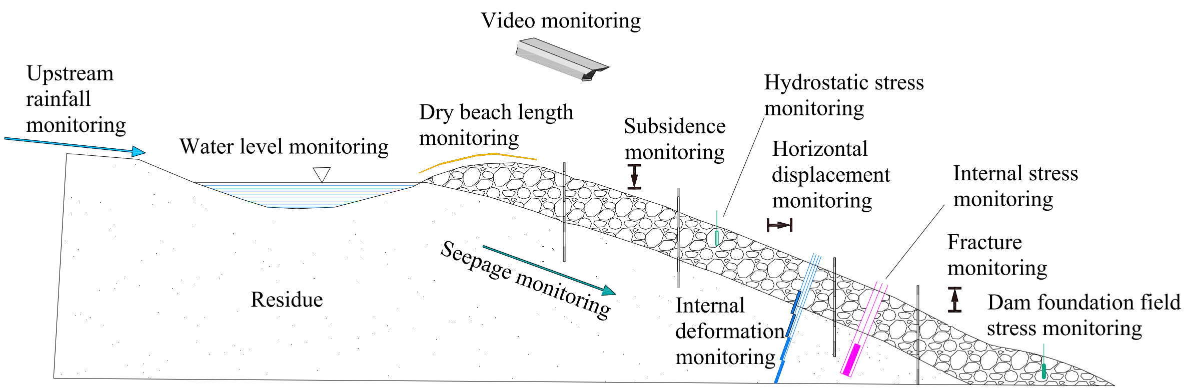

FIGURE 2. The schematic diagram for the tailings dam with safety monitoring.

platform through the calculation of parameters and indexes, which are necessary and significant for the safety analysis of the tailings dam. Finally, the calculation results will guide the practical applications. The hierarchical structure of PSRMNS-IOTCC for the tailings dam is shown in Fig. 1, where the four layers are the sensing layer, the IOT layer, the CC layer, and the application layer.

A. THE SENSING LAYER

The sensing layer is not only a fundamental layer, but also an essential layer of the PSRMNS-IOTCC, which contains hydrostatic pressure monitoring, upstream rainfall monitoring, water level monitoring, dry beach length monitoring, horizontal displacement monitoring, internal deformation and stress monitoring, seepage monitoring, fracture monitoring, and subsidence monitoring. The schematic diagram of safety monitoring for the tailings dam is shown in Fig. 2, where the monitoring contents are exhibited clearly and particularly. A mass of data that reflect and explain the physical situations are obtained from various kinds of sensors, such as the water level sensor, water pressure sensor, displacement sensor, and stress sensor. The sensors used in the sensing layer are wireless sensors, which can work as nodes for the wireless sensors network with low power consumption and time synchronization. In addition, they can communicate with each other continuously for dozens of hours through the wireless medium, which are more stable and efficient compared to the sensors in the traditional sensors network.

B. THE IOT LAYER

The IOT layer is the second layer of the PSRMNS-IOTCC, which consists of the remote control, data acquisition system, radio access, wireless sensor network, distributed stations, the time synchronization clock, and wireless network. Based on the received data from the sensing layer, the data can be uploaded to the cloud computing platform through the Internet for further process. Thus, it can be seen that the IOT layer is the connection bridge between the sensing layer and the CC layer. As the application of wireless sensor network, distributed stations, and wireless network, there will be an obvious improvement for the speed and stability of data transmission, which is exactly the basis for the real-time monitoring and pre-alarm system of the tailings dam.

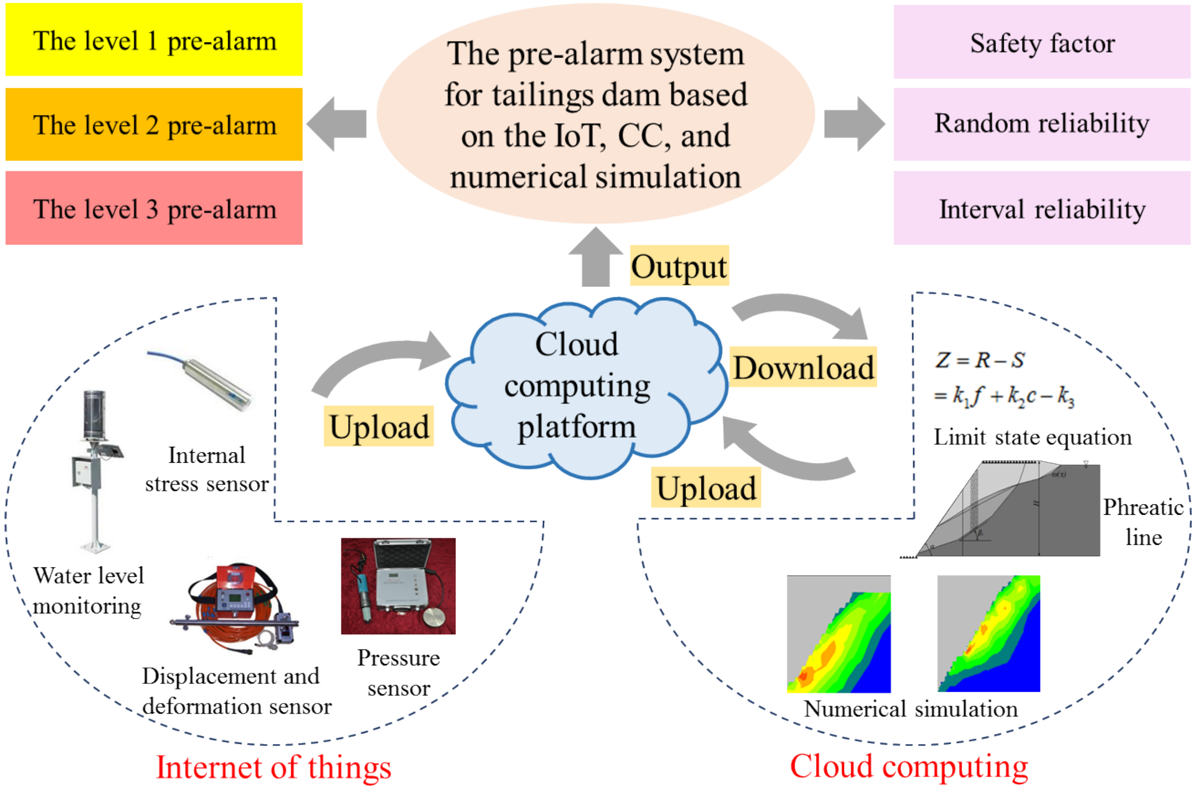

FIGURE 3. The real-time pre-alarm platform of the tailings dam. The 3 pre-alarm levels are level 1, level 2, and level 3, which represent the slight safety hazard, middle safety hazard, and serious safety hazard, respectively.

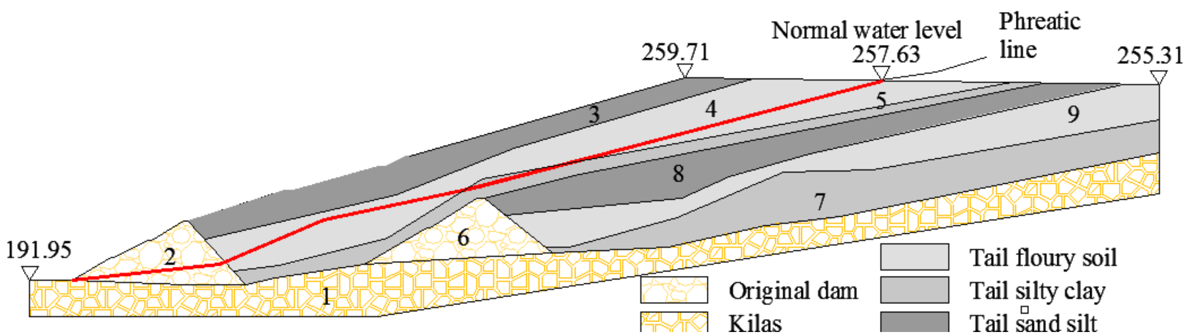

FIGURE 4. The physical composition of the tailings dam. The original dam, kilas, tail floury soil, tail silty clay, and tail sand silt are represented with different colors.1 to 9 indicate region ID, their physical and mechanical parameters are listed in Table 1.

C. THE CC LAYER

The CC layer includes the prediction of phreatic line, limit state equation, numerical simulation, safety factor, random reliability, and interval non-probabilistic reliability, which is the third layer of PSRMNS-IOTCC. With the data transmitted from the IOT layer, the important parameters including the phreatic line, safety factor, random reliability, and interval non-probabilistic reliability can be solved through the cloud computing platform. Besides, these calculation results are also stored in this cloud computing platform, which means that the calculated results can be downloaded from the platform whenever the need arises. Therefore, a great convenience and sufficient data will be provided for the safety monitoring of the tailings dam.

D. THE APPLICATION LAYER

The top layer of PSRMNS-IOTCC is the application layer, which includes the intelligent control, sound-light pre-alarm, visualization status of tailings dam, and emergency rescue plan. According to the output results from the cloud computing platform, the safety degree can be evaluated into three levels, which are the level 1 pre-alarm, the level 2 pre-alarm, and the level 3 pre-alarm, respectively. The level 1 represents the slight safety hazard, the level 2 represents the middle safety hazard, and the level 3 represents the serious safety hazard. Fig. 3 shows the real-time pre-alarm platform, which is based on the internet of things, cloud computing, and numerical simulation.

TABLE 1. The physical and mechanical parameters of the tailings dam.

Region ID	Weight (kN/m3)	Cohesion (kPa)	Internal friction angel (°)	Friction coefficient f
1	23.0	5.1	50	1.1918
2	22.0	4.0	35	0.7002
3	19.6	9.0	21	0.3839
4	19.6	9.0	21	0.3839
5	19.6	8.0	28	0.5317
6	22.0	4.0	35	0.7002
7	19.0	12.0	19	0.3443
8	19.6	10.0	25	0.4663
9	19.6	10.0	25	0.4663

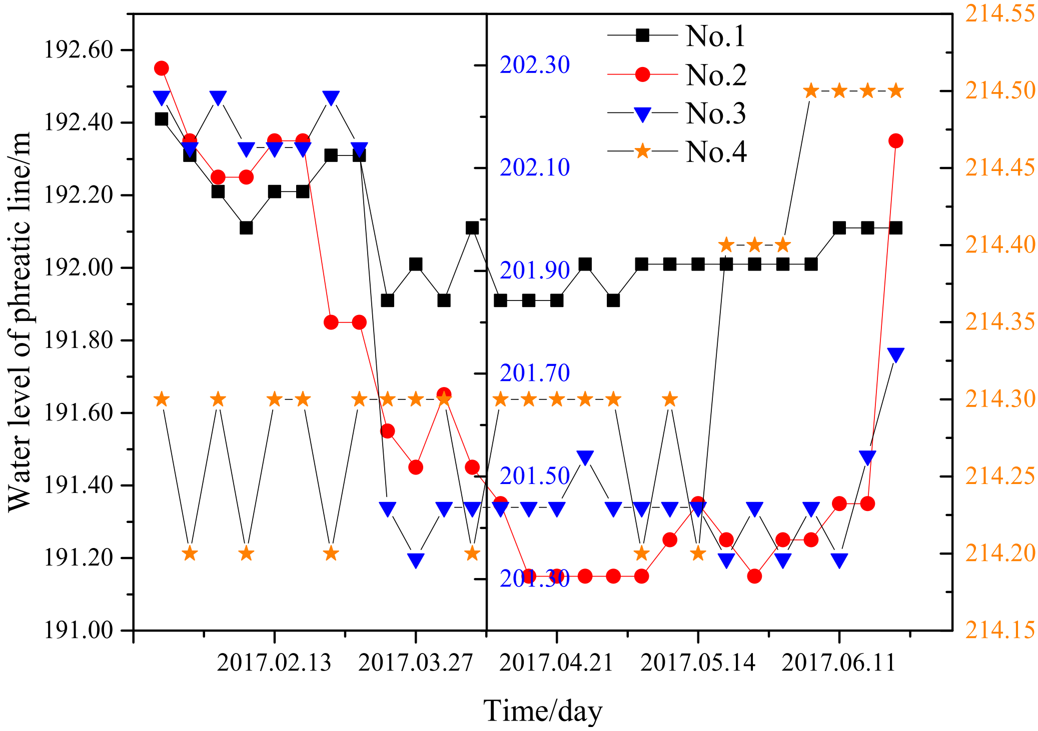

FIGURE 5. The variation tendency for the water level of the phreatic line. The left Y-axis shows the results of the No.1 and No.2 monitoring points, the middle Y-axis shows the results of the No.3 monitoring point, the right Y-axis shows the results of the No. 4 monitoring point.

III. A CASE STUDY AND DISCUSSION

The sensor networks are arranged to monitoring the physical data of the tailings dam. The data of the displacement of the monitoring points, the sedimentation of the monitoring points, and the water level of the monitoring holes are obtained. The physical composition of the tailings dam is shown in Fig. 4, and the main physical and mechanical parameters of the tailings dam are listed in Table 1. The variation tendency for the water level of the phreatic line is shown in Fig. 5.

The phreatic line is predicted by training the data of water level of the observation holes using coupled model of grey model and generalized regression neural network (GM-GRNN) in the cloud platform. The specific procedure of the coupled model is shown in Fig. 6. Then, the equation of phreatic line for the future state can be obtained.

The specific application steps of coupled model GM-GRNN are stated below:

- In the GM, it is feasible to obtain the GM(1, 1) through the data training with the established model, where the data contain the monitoring time and the water level of monitoring hole of the tailings dam.
- Based on the obtained grey model, the future variation for water level of monitoring hole of the tailings dam

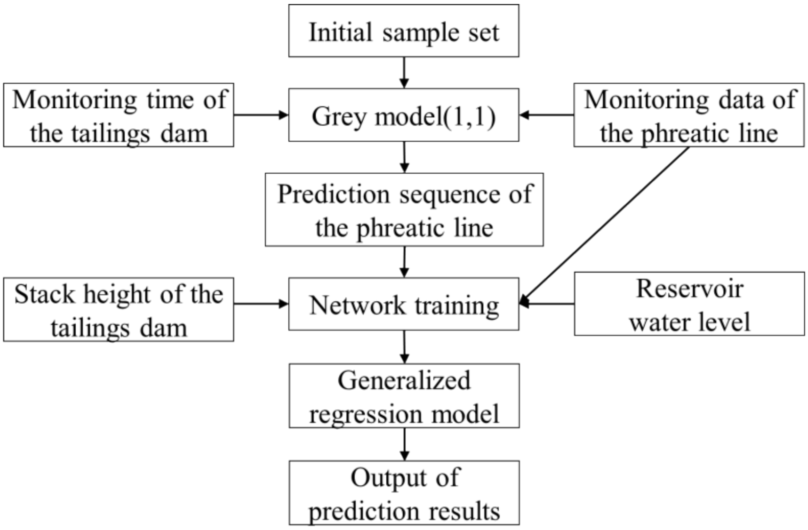

FIGURE 6. The application flowchart of the coupled model. The grey and generalized regression neural network is applied to predict the phreatic line of fiture state, based on the monitoring data of the phreatic line.

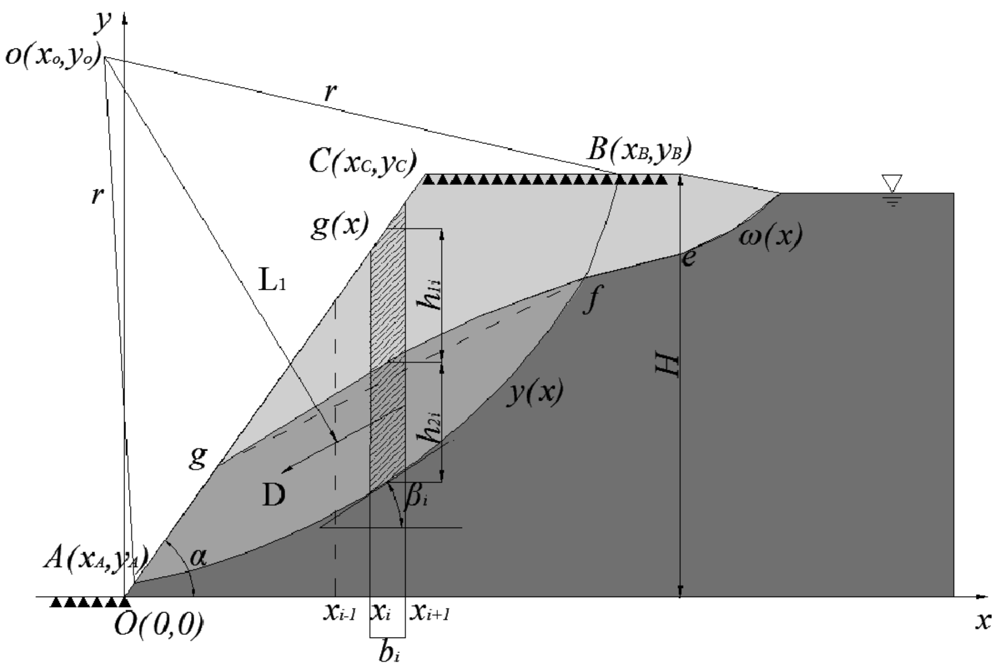

FIGURE 7. Slope section of the arc of destruction with considering the impact of phreatic line.

can be solved. Then, the prediction sequence will be obtained.

- Taken the prediction value, dam height, and reservoir water level as the input data, the generalized regression neural network is trained with the data of initial water level of monitoring hole are taken as the expectations. According to the grey prediction values of the months to be predicted, dam height, and reservoir water level, the corresponding output factors of water level can be obtained, which are exactly the output of network. Then, the GRNN model can be established. As the performance of the network is also affected by the smoothing factor, the optimal value will be determined through repeated calculation.
- In the established GRNN model, the prediction value for water level of monitoring hole with sufficient precision can be obtained, when the prediction values of grey model for the years to be predicted, dam height, and reservoir water level are input. Then, the prediction of phreatic line will be accomplished smoothly.

The numerical simulation model is established through considering the predicted equation of phreatic line, the limit equilibrium state parameters, and reservoir water level. The main solved processes for the main parameters, which

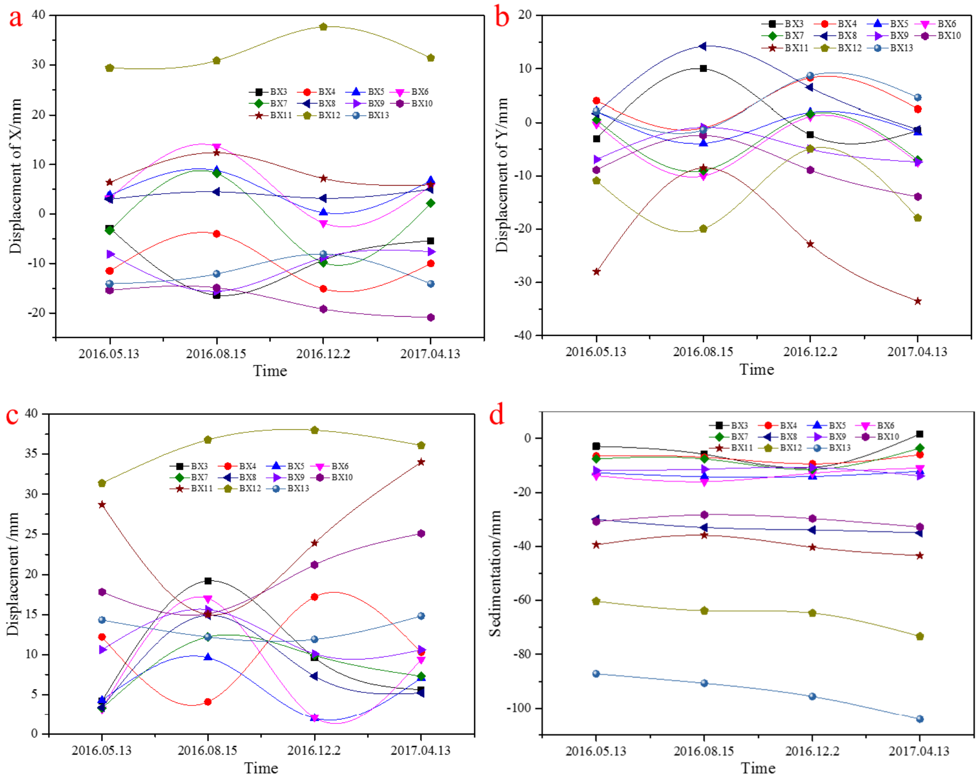

FIGURE 8. The monitoring results of the displacement sensors. The graphs a, b, c, and d indicate the displacement of X, the displacement of Y, the composite displacement, and the subsidence of the displacement sensors, respectively.

include the safety factor, random reliability, and interval non-probabilistic reliability, are presented following. As shown in Fig. 7 [23], the equations of the sliding face, the slope, and the phreatic line are $f(x)$, $g(x)$, and $\omega(x)$, respectively. W indicate the area of the part $fgBf$ modeled by the phreatic line, the slope and the sliding face. D is the hydraulic force acting on the part $fgBf$. The arm of the hydraulic force to the center of sliding face is L_1. h_{1i} and h_{2i} indicate the length of the vertical tailings above and below the phreatic line respectively. c and φ are the cohesion and the internal friction angel. γ, γ_w, and γ_{sat} are the mean unit weight of the tailings, the unit weight of the water, and the saturated unit weight of the tailings.

The equation of sliding face can be expressed as

$$f(x) = 135 - \left(168.28^2 - (x-75)^2\right)^{0.5} \tag{1}$$

The equation of the slope can be expressed as

$$g(x) = \begin{cases} 0.518248x & x \le 54.8 \\ 0.313719x + 11.2082 & 54.8 \le x \le 182.94 \\ 0.25263x + 22.3839 & 182.94 \le x \le 291.32 \end{cases} \tag{2}$$

The equation of the phreatic line can be expressed as

$$\omega(x) = \begin{cases} 0.11143x & x \le 73.23 \\ 0.427934x - 23.1776 & 73.23 \le x \le 122.56 \\ 0.208971x + 3.65846 & 122.56 \le x \le 196.35 \\ 0.26117x - 6.59069 & 196.35 \le x \le 387.49 \end{cases} \tag{3}$$

The limit state equation of the tailings dam failure can be written as

$$Z = R - S = k_1 f + k_2 c - k_3 \tag{4}$$

where:

$$R = r\int_{x_B}^{x_A} \{\frac{c}{\cos\beta} + \{[\gamma[g(x)-\omega(x)] + \gamma_{sat}[\omega(x)-y(x)]]\cos\beta - \frac{\gamma_w[\omega(x)-y(x)]}{\cos\beta}\}f\}dx \tag{5}$$

$$S = \int_{x_B}^{x_A} (x-x_0)\left[\gamma[g(x)-\omega(x)] + \gamma_{sat}[\omega(x)-y(x)]\right]dx + L_1 D \tag{6}$$

$$k_1 = r\int_{x_B}^{x_A} \{[\gamma[g(x)-\omega(x)] + \gamma_{sat}[\omega(x)-y(x)]]$$

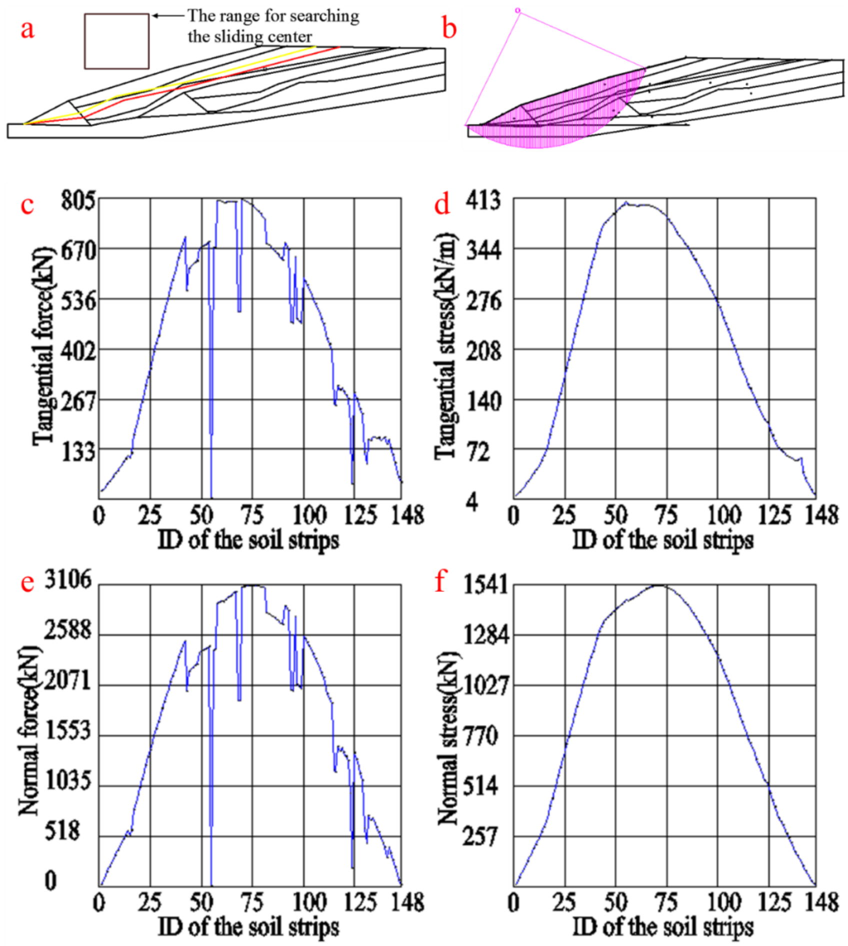

FIGURE 9. The key parameters and the numerical stimulation in the cloud platform of the PSRMNS-IOTCC. The graphs a and b indicate the numerical simulation. The graphs c, d, e, and f indicate tangential force, tangential stress, normal force, and normal stress for the soil strips, respectively.

$$\frac{\sqrt{r^2-(x-x_0)^2}}{r}-\frac{r\gamma_w[\omega(x)-y(x)]}{\sqrt{r^2-(x-x_0)^2}}\}dx \tag{7}$$

$$k_2 = 2r^2 \arcsin\frac{\sqrt{(x_B-x_A)^2+(y_B-y_A)^2}}{2r} \tag{8}$$

$$k_3 = \int_{x_B}^{x_A}(x-x_0)\left[\gamma[g(x)-\omega(x)]+\gamma_{sat}[\omega(x)-y(x)]\right]dx + L_1 D \tag{9}$$

The safety factor and random reliability can be expressed as (10) and (11).

$$k = \frac{R}{S} \tag{10}$$

$$P_s = 1-\phi(-\beta) = \phi(\beta) \tag{11}$$

According to the interval value standardization method, the limit state equation (4) is transformed into standard form, namely,

$$Z = R - S = k_1 \times \left(f^{\mathrm{c}} + f^{\mathrm{r}}\delta_f\right) + k_2 \times \left(c^{\mathrm{c}} + c^{\mathrm{r}}\delta_c\right) - k_3 \tag{12}$$

where: R and S indicates resistance and sliding load.

According to above theory and processes, the safety factor, random reliability, and interval non-probabilistic reliability can be solved out using the cloud platform of the PSRMNS-IOTCC.

From the IOT layer of the PSRMNS-IOTCC, Fig. 8 shows that the maximum displacements of X-axis and Y-axis are about 36 mm and 15 mm, respectively. The composite displacement is about 37 mm. The subsidence reaches greater than −100 mm. From the CC layer of the PSRMNS-IOTCC, the dynamic safety factor, random reliability, and interval non-probabilistic reliability can be obtained, which are 2.143, 1.184, and 0.798, respectively. Some key parameters and the numerical stimulation in the cloud platform of the PSRMNS-IOTCC are shown in Fig. 9. Combined with the trend of real-time monitoring deformation, calculated dynamic safety factor, random reliability, and interval non-probabilistic reliability, the random reliability and the safety factor show that the tailings dam is in a reliable status, while the interval non-probabilistic reliability indicates that the tailings dam is likely to lose the stability condition, for which that the interval non-probabilistic reliability is more conservative than the other two parameters. According to the results of the interval non-probabilistic reliability and the subsidence with greater than -100 mm, the safety level is evaluated as level 1. Therefore, the measurements corresponding to the level 1 pre-alarm condition should be prepared and performed, to ensure the safety of the tailings dam.

The developed PSRMNS-IOTCC takes full advantages of the internet of things (IOT) and cloud computing (CC), which have the characteristics of fast data transmission speed and cloud data integration platform, to achieve the real-time monitoring for the safety of the tailings dam through the integration and mutual validation with plenty of key information. Based on the cloud platform and monitored data of phreatic line, the trend of tailings dam can be predicted using the grey neural network. Combined with the calculated safety factor, random reliability, and interval non-probabilistic reliability, it is feasible to predict the future stability conditions considering the dynamic phreatic line for the tailings dam.

IV. CONCLUSIONS

As the continuous improvement of resources mining industry, the safety of tailings dam is becoming a significant and urgent problem need to be solved. The tailings dam is one of human-caused hazard sources with high potential energy. Therefore, the PSRMNS-IOTCC was developed for the tailings dam using the internet of things and could computing. Based on various kinds of sensors laid at specific places in the tailings dam, the plenty of data, which explain the physical conditions, including the phreatic line, water level of the monitoring hole, internal and external deformation, rainfall, and reservoir water level can be obtained from the sensing layer. Then, the wireless network can be established for the tailings dam with multiple key information. Furthermore, the future equation of phreatic line can be solved on the basis of the real-time monitoring data of current phreatic line using the coupled grey and generalized regression neural network, with the established cloud computing platform, which means that the future state of phreatic line can be predicted reasonably. The key parameters including the dynamic safety factor, random reliability, and interval non-probabilistic reliability will be solved through the integration of the real-time monitoring data, as well as internal and external deformation of the tailings dam. The case study shows that the dynamic safety factor, random reliability, interval non-probabilistic reliability, and subsidence are 2.143, 1.184, 0.798, and greater than -100 mm, respectively. Considering the conservatism of the interval non-probabilistic reliability and the great subsidence of the tailings dam, it should be evaluated as the level 1 pre-alarm, to make sure the stability and safety of the tailings dam. Though the data analysis and practical application, it is proved that the developed PSEMNS-IOTCC can not only achieve real-time monitoring efficiently for the tailings dam, but also can calculate the key parameters to perform the evaluation of pre-alarm level, which is a novel idea and effective application for the safety assurance of the tailings dam.

REFERENCES

[1] A. Anon, "Review of tailings dam failure," *Int. Water Power Dam Construction*, vol. 53, no. 5, pp. 40–42, 2001.

[2] H. Zhang, Y. Zhao, and X. Li, "Research on monitoring of tailing reservoirs based on the Internet of Things—A case study of huangmailing phosphorus chemical tailing reservoir," *Saf. Environ. Eng.*, vol. 22, no. 6, pp. 143–150, Dec. 2015.

[3] K. J. Witt and M. Schönhardt, "Tailings management facilities-risks and reliability," Eur. RTD Project, Sep. 2004. [Online]. Available: http://www.tailsafe.com/pdf-documents/TAILSAFE_Risk_and_Reliability.pdf

[4] J. Li, C. P. Li, C. M. Li, and Z. X. Li, "Forecasting of infiltration route in tailings dam by support vector regression," *J. Saf. Sci. Technol.*, vol. 5, no. 1, pp. 76–78, Jan. 2009.

[5] B. Yuan, F. Y. Wang, Y. J. Jin, and W. D. Zhao, "Study on the model for tailings dam breaking and its application," *China Saf. Sci. J.*, vol. 18, pp. 169–172, Apr. 2008.

[6] F. Y. Wang, "Research on stability analysis and comprehensive assessment of the tailing dam based on the uncertainty theory," Ph.D. dissertation, Disaster Prevention Reduction Eng., Central South University, Changsha, China, 2009.

[7] Q. Jiang and Y. Tang, "A general approximate method for the groundwater response problem caused by water level variation," *J. Hydrol.*, vol. 529, pp. 398–409, Oct. 2015.

[8] Y. Tang, Q. Jiang, and C. Zhou, "Approximate analytical solution to the Boussinesq equation with a sloping water-land boundary," *Water Resour. Res.*, vol. 52, no. 4, pp. 2529–2550, Apr. 2016.

[9] G. E. Blight, "Destructive mudflows as a consequence of tailings dyke failures," *Proc. Inst. Civil Eng.-Geotech. Eng.*, vol. 125, no. 1, pp. 9–18, Jan. 1997.

[10] S. Moxon, "Failing again," *Int. Water Power Dam Construction*, vol. 51, no. 5, pp. 16–21, Jan. 1999.

[11] M. Rico, G. Benito, and A. Díez-Herrero, "Floods from tailings dam failures," *J. Hazardous Mater.*, vol. 154, nos. 1–3, pp. 79–87, Jun. 2008.

[12] H. G. Wei, L. Xing, and L. Xu, "Study on monitoring and warning system for safety detection of tailings reservoir," *Fujian Comput.*, vol. 26, no. 4, pp. 99–100, Aug. 2010.

[13] Y. L. Li, "Application of full-site elevation digital model with triangle altimetric survey in sinkage monitoring for Lixi tailings fill dam," *China Molybdenum Ind.*, vol. 32, no. 3, pp. 37–39, Jun. 2008.

[14] J. M. Duncan, "Factors of safety and reliability in geotechnical engineering," *J. Geotech. Geoenviron. Eng.*, vol. 126, no. 4, pp. 307–316, Apr. 2000.

[15] G. Wang and Z. Ma, "Hybrid particle swarm optimization for first-order reliability method," *Comput. Geotech.*, vol. 81, pp. 49–58, Jan. 2017.

[16] S.-X. Guo and Z.-Z. Lu, "A non-probabilistic robust reliability method for analysis and design optimization of structures with uncertain-but-bounded parameters," *Appl. Math. Model.*, vol. 39, no. 7, pp. 1985–2002, Apr. 2015.

[17] B. Y. Ni, C. Jiang, and X. Han, "An improved multidimensional parallelepiped non-probabilistic model for structural uncertainty analysis," *Appl. Math. Model.*, vol. 40, nos. 7–8, pp. 4727–4745, Apr. 2016.

[18] M. S. Chowdhury, C. M. Song, W. Gao, and C. Wang, "Reliability analysis of homogeneous and bimaterial cracked structures by the scaled boundary finite element method and a hybrid random-interval model," *Struct. Saf.*, vol. 59, pp. 53–66, Mar. 2016.

[19] Y. Ben-Haim, S. Cogan, and L. Sanseigne, "Usability of mathematical models in mechanical decision processes," *Mech. Syst. Signal Process.*, vol. 12, no. 1, pp. 121–134, Jan. 1998.

[20] T. Jiang, J.-J. Chen, P.-G. Jiang, and Y.-F. Tuo, "A one-dimensional optimization algorithm for non-probabilistic reliability index," *Chin. J. Eng. Mech.*, vol. 24, no. 7, pp. 23–27, Jul. 2007.

[21] S. X. Guo, Z. Z. Lu, and Y. Feng, "A non-probabilistic model of structural reliability based on interval analysis," *Chin. J. Comput. Mech.*, vol. 18, no. 1, pp. 56–60, Feb. 2001.

[22] L. J. Dong and X. B. Li, "Interval parameters and credibility of representative value of rock tensile and compression strength tests," *Chin. J. Geotech. Eng.*, vol. 32, no. 12, pp. 1969–1974, Dec. 2010.

[23] L. Dong, D. Sun, and X. Li, "Theoretical and case studies of interval non-probabilistic reliability for tailing dam stability," *Geofluids*, vol. 2017, Sep. 2017, Art. no. 8745894, doi: 10.1155/.2017/8745894.

[24] L. Dong, D. Sun, X. Li, and Z. Zhou, "Interval non-probabilistic reliability of a surrounding jointed rockmass in underground engineering: A case study," *IEEE Access*, vol. 5, Sep. 2017, to be published, doi: 10.1109/ACCESS.2017.2743115.
[25] G. Han, L. Liu, S. Chan, R. Yu, and Y. Yang, "HySense: A hybrid mobile CrowdSensing framework for sensing opportunities compensation under dynamic coverage constraint," *IEEE Commun. Mag.*, vol. 55, no. 3, pp. 93–99, Mar. 2017.
[26] R. Liu and J. Wang, "Internet of things: Application and prospect," in *Proc. MATEC Web Conf.*, Zhengzhou, China, 2017, Art. no. 02034.
[27] G. Han, L. Liu, J. Jiang, L. Shu, and G. Hancke, "Analysis of energy-efficient connected target coverage algorithms for industrial wireless sensor networks," *IEEE Trans. Ind. Informat.*, vol. 13, no. 1, pp. 135–143, Feb. 2017.
[28] G. Han, J. Jiang, C. Zhang, T. Q. Duong, M. Guizani, and G. K. Karagiannidis, "A survey on mobile anchor node assisted localization in wireless sensor networks," *IEEE Commun. Surveys Tuts.*, vol. 18, no. 3, pp. 2220–2243, 3rd Quart., 2016.
[29] G. Han, J. Jiang, M. Guizani, and J. J. P. C. Rodrigues, "Green routing protocols for wireless multimedia sensor networks," *IEEE Wireless Commun.*, vol. 23, no. 6, pp. 140–146, Dec. 2016.
[30] L. Dong and X. Li, "Comprehensive models for evaluating rockmass stability based on statistical comparisons of multiple classifiers," *Math. Problems Eng.*, vol. 2013, Sep. 2013, Art. no. 395096.
[31] L. J. Dong, X. B. Li, and G. N. Xie, "Nonlinear methodologies for identifying seismic event and nuclear explosion using random forest, support vector machine, and naive Bayes classification," *Abstract Appl. Anal.*, vol. 2014, Feb. 2014, Art. no. 459137.
[32] L. J. Dong, J. Wesseloo, Y. Potvin, and X.-B. Li, "Discriminant models of blasts and seismic events in mine seismology," *Int. J. Rock Mech. Mining Sci.*, vol. 86, pp. 282–291, Jul. 2016.

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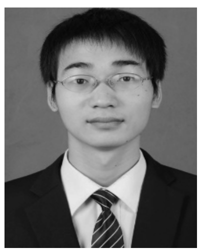

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