An Integrated Visualization Framework to Support Whole-Process Management of Water Pipeline Safety

Donghai Liu[a], Junjie Chen[a], Shuai Li[b], Wei Cui[a]

[a] State Key Laboratory of Hydraulic Engineering Simulation and Safety, Tianjin University, 135 Yaguan Road, Tianjin 300350, China

[b] Department of Civil and Environmental Engineering, the University of Tennessee, Knoxville, 851 Neyland Dr. Knoxville, TN, the United States.

Liu, D., Chen, J., Li, S., & Cui, W. (2018). An Integrated Visualization Framework to Support Whole-Process Management of Water Pipeline Safety. *Automation in Construction*, 89:24-37. Doi: 10.1016/j.autcon.2018.01.010.

Abstract

Timely assessment of structural conditions of water diversion pipelines and taking necessary precautions are essential to ensure the operational safety of large water diversion structures. This paper presents an integrated visualization framework to support the safety management of water diversion pipelines. This holistic framework streamlines data collection, data analysis, warning issuance, and decision-making support in an integrated platform, which improves the automation level of safety management and the efficiency of emergency response. A system prototype was developed based on the proposed framework and implemented in a water supply project in Tianjin, China. The system prototype can automatically assess the structural condition of water diversion pipelines and issue corresponding warnings to relevant professionals, and provide visual cues and a set of useful functions to support decision-making. This system prototype and its implementation validate the applicability and efficacy of the proposed framework.

Keywords: Water diversion projects; Structural condition assessment; Safety management; Whole-process management; Visualization.

1. Introduction

To counter the threats associated with the uneven distribution of water resources, China has launched a number of water diversion projects such as the South-to-North Water Diversion Project to alleviate severe water shortages in certain areas [1]. The South-to-North Water Diversion Project has three routes in the Eastern, Central, and Western China that respectively divert water from the lower, middle, and upper reaches of the Yangtze River. This long-distance and inter-basin water diversion project also connects four major rivers in China: Yangtze River, Huai River, Yellow River, and Hai River. These water diversion projects have improved urban water supply and water quality, thereby ensured the well-being of the people, the vitality of the economy, and the prosperity of the society.

Structural damages to the water diversion pipelines can result in disastrous humanitarian, social, economic, and ecological consequences. Therefore, it is essential to assess the structural conditions of the pipelines in a timely manner and take immediate actions to handle emergency situations. Instruments have been developed to monitor the structural conditions of water diversion pipelines [2-4], but the management information system (MIS) and safety management practice are still insufficient to realize automatic condition assessment and timely emergency response.

There are two main limitations in the current practice. First, the manual processing of monitoring data and the lack of visual cues make the identification of abnormalities in pipelines time-consuming, which hinders the decision-makings in the event of an emergency. Second, the data collection, data analysis, warning issuance, and decision support have not been seamlessly integrated in the safety management process, and the functions in existing MIS are not comprehensive to fulfill the whole-process management of pipeline safety. Such isolated management process and limited system functions will result in potential safety issues not being identified and emergency responses being delayed. To address these two challenges, an integrated visualization framework is proposed in this study to support the whole-process management of structural safety for water diversion projects.

2. Limitations in Current Practice

This section reports the limitations in the current practice of pipeline safety management. From the technical perspective, the first limitation is the manual processing of a large amount of monitoring data. The advancements of sensing technologies and mobile communication networks [5-7] have made data collection automated and rapid, generating a large amount of monitoring data. Manually processing the data is inefficient and time-consuming, and thus is incapable of achieving automated condition assessment and timely emergency response. The second limitation is the lack of a geo-referenced visual environment and comprehensive analysis tools in the existing MIS [8, 9] to support decision-makings. Most often, the monitoring data are not directly coupled with geographic coordinates, thus, decision-makers have to refer to non-intuitive design drawings to locate abnormalities and analyze in-situ environments. In addition, in the absence of scientific analysis, engineers solely rely on their experiences to make decisions in emergency situations.

From the organizational and managerial perspective, the first limitation is that the critical tasks in pipeline safety management, i.e. data collection, data analysis, warning issuance, and decision support, have not been seamlessly integrated. This incoherent management process may weaken the competent department’s ability to identify a potential safety hazard and significantly delay the response action. Studies have been conducted on data analysis and decision support in pipeline safety management. Examples include safety diagnosis of hydraulic structures based on data mining [10, 11], risk assessment for water pipelines [12, 13], mobile computing technologies for safety inspection [14], and failure mode of pre-stressed concrete pipe [15-17]. However, the existing studies mainly focused on the development of a single function for a single task in the safety management. None of them have created a holistic frameowrk to streamline the whole safety management process of water diversion projects.

3. Review of Existing Techniques

3.1. Analysis of monitoring data based on data mining

Data mining techniques have been used for analyzing safety monitoring data in hydraulic engineering [10, 11], building construction [18, 19], and aerospace engineering [20, 21]. To enable intelligent and automatic structure safety analysis, the integration of data mining and cloud computing was explored in [22, 23]. However, the existing technologies are not readily applicable in water diversion projects. In the current practice, the process of data collection, data analysis and warning issuance have not been automated and streamlined. For example, X is a water diversion project located in Zhejiang Province, China. Although the project has adopted a safety monitoring system that uses a general packet radio service (GPRS) cellular network to obtain monitoring data remotely and automatically, the subsequent data analysis is performed in a manual and off-line way. As such, it is very difficult to frequently analyze the monitoring data. Hence, abnormalities may not be identified in a timely manner, posing significant risks to the water diversion pipelines. In addition, due to the lack of a warning issuance mechanism, this system cannot inform engineers and professionals of abnormalities and emergencies.

3.2. Visualization based on GIS and street view

Geographic information system (GIS) has been used to visualize information and support decision-making. For instance, different colors were used to represent the risk degrees of pipeline in GIS environment, and aerial photos were overlaid to improve the visualization [13, 24, 25]. Coffey et al. [26] used GIS to enhance the pipeline management and analysis. Liu and Issa [27] integrated three-dimensional (3D) building information modeling and two-dimensional (2D) GIS to realize 3D visualization of underground pipeline systems. Wu et al. [28] applied 3D GIS in dam safety monitoring and developed a visualized management information system. In addition, Google street views were also used to assess large-scale vegetation [29], environmental contributions to pedestrian injury [30], and species habitat [31].

The integration of 3D GIS and street view in structure safety management can improve management efficiency and provides intuitive visual cues for decision-makings. The fusion of safety monitoring data and geographic information allows users to locate the potential abnormalities in the 3D scenes that are archived in the GIS platform. Moreover, after an emergency occurs, engineers can utilize the 3D GIS and street views to analyze the in-situ environment online (e.g. to check surrounding topography, available transportation routes, and manhole locations), which can assist the plan of emergency responses. However, the previous studies have not explored the integration of 3D GIS and street view in water diversion projects.

3.3. Numerical simulation

Numerical simulation has been widely applied in water diversion projects. Oh et al. [32] used numerical method to investigate the discharge performance of sluice passageway. Chen et al. [33] conducted numerical simulation to analyze the damage mode of concrete gravity dam under close-in explosion. In [15-17], finite-element software was used to study the failure mode and rehabilitation method of pre-stressed concrete cylinder pipe (PCCP).

Numerical simulation is a powerful tool to support decision-makings, since it can simulate mechanical responses of structure under various working conditions without carrying out physical experiments. However, due to the complicate operation process, it is difficult to directly incorporate the numerical simulation into the safety management process. In order to fully support decision-makings in water diversion projects, secondary development is necessary for the numerical simulation tool; and the developed product should be included as an integral part of the management information system.

4. Framework for Whole-Process Management of Water Pipeline Safety

In this study, 3D GIS, street view, data mining, and numerical simulation are integrated to streamline the data collection, data analysis, warning issuance, and decision support in a holistic framework for the safety management of water diversion pipelines.

4.1. Procedure of whole-process safety management

The entire process of safety management consists of four steps, i.e. data collection, data analysis, warning issuance, and decision-making support. Shown in Figure 1, the proposed safety management procedure emphasizes the automation of safety monitoring and assessment as well as the integration of automated operation with human intervention.

(1) Automatic collection of monitoring data

The collected data have two sources: 1) monitoring data, such as water pressure, deformation, and crack, remotely and periodically collected by the automatic monitoring system; 2) settlement data and photos collected during on-site inspection.

(2) Online analysis and safety assessment

The collected data are automatically analyzed at a predetermined time interval (e.g. once a day) to detect potential abnormalities based on methods such as trend recognition and neural network model. An evaluation system is developed to determine the risk level of the structure based on the analysis of monitoring data.

(3) Real-time warning issuance

When the risk of a pipeline segment reaches a certain level, real-time warnings will be automatically issued by phone messages and emails to ensure that engineers and professionals can receive the warnings in a timely manner.

(4) Decision-making support

In the event of an emergency, engineers and professionals will conduct a comprehensive safety assessment and make reaction and contingency plan. In this stage, computer software should be fully utilized to support decision-makings. For example, GIS and numerical simulation can be used to analyze the surrounding environment of abnormalities and determine the optimal water supply plan under adverse conditions.

4.2. Framework architecture

As shown in Figure 2, a holistic framework is proposed to support the whole-process management of structure safety for water diversion projects. The proposed framework consists of four systems, i.e. safety data acquisition system (SDAS), safety analysis and assessment system (S2AS), simulation and warning system (SAWS), and 3D visualized management system (3DMS). SDAS, corresponding to the data acquisition stage of the safety management process, consists of the automatic safety monitoring module and the personal digital assistant (PDA) in-situ inspection module; S2AS corresponds to the data analysis stage; SAWS consists of the warning issuance module and the numerical simulation module, respectively corresponding to the warning issuance stage and the decision support stage; 3DMS enables data query and data management in normal operation, and its geo-reference and visualization capability can be used to support decision-makings after an emergency occurs.

In Figure 2, the green arrow lines represent the data flow during the period of automatic operation. SDAS integrates multi-source safety monitoring data with different formats into one uniform database and provides data access interface to the other three systems. S2AS periodically and automatically analyzes the data collected by SDAS, in which data mining techniques are used to recognize abnormalities and evaluate structure safety. If the risk levels reach certain thresholds, the abnormalities will be sent to the warning issuance module of SAWS, which will then inform the competent department via phone messages and emails. In addition, the warning messages will also be issued to 3DMS to help engineers to locate the abnormalities in 3D environment.

Upon the receipt of warning messages, engineers and professionals will intervene (data flow represented by the red arrow lines in Figure 2). In this stage, the proposed framework can support decision-making from two aspects. First, the numerical simulation module provides scientific analysis for decision makers to adjust water supply plan under emergency. This module maps the load information reflected by the monitoring data to an established finite element (FE) model, and considers the time-varying effects of material mechanical properties. As such, realistic simulation can be conducted to assess the structure safety under different supply flows. Second, 3DMS can help engineers to locate the potential safety issues by positioning abnormal data points. In addition, the system combines street views and 3D GIS to enable vivid visualization of in-situ environment of abnormal locations to provide decision makers detailed insights.

5. System Prototype Development

To validate the applicability of the proposed framework, a system prototype was developed and implemented on a water supply project in Tianjin, China. This project is part of the auxiliary project in the middle route of China's South-to-North Water Diversion Project. The main structures under consideration are pre-stressed concrete cylinder pipes (PCCP) and steel pipes. This section elaborates the development and implementation of the system prototype.

5.1. SDAS

The system uses the hardware and software developed by Geokon® [9] to automatically and remotely collect safety monitoring data (e.g. internal/external water pressure, deformation and crack). Data is collected at a user-defined time interval (e.g. once a day) by using the data management software installed on a server [34]. The collected data is transmitted to the ACCESS database on the server through GPRS, 3G or 4G networks. In addition, the settlement data are manually collected by leveling surveying. Figure 3 illustrates how SDAS integrates the above data. The database server carries two database platforms: ACCESS and SQL Server. ACCESS is the designated software of Geokon® automatic monitoring system; and SQL Server is used by the four subsystems in the prototype. The main source of monitoring data for safety analysis is the data collected by the Geokon® system, thus it should be seamlessly integrated into the SQL Server. To this end, an interface program is developed to obtain the updated data from the ACCESS database at the predetermined interval (e.g. once a day).

PDA in-situ inspection module was designed to upload settlement data collected by leveling surveying and geo-registered photos captured during inspection. In case of poor mobile communication signal, the monitoring data and field photos will be stored in the device and will be re-uploaded when the internet signal is recovered. The module was developed based on the Eclipse platform and the operation environment is Android.

5.2. S2AS

S2AS aims to recognize abnormalities by analyzing the massive monitoring data using data mining techniques such as statistics analysis and neural network, and to assess the risk level of structure safety based on the detected abnormalities. Trend recognition, extreme value recognition, neural network model, and monitoring index assessment are used to recognize abnormalities.

(1) The trend recognition method identifies abnormalities by comparing the current data trend with the overall trend and examining to what extent the current trend matches the overall trend. The data trend can be defined by the notion of "succession". The elements in a continuous data series $\{y_n\}$ can be categorized into two groups by the mean value ($\bar{y}$) of the series: those greater than $\bar{y}$ are defined as "positive" while those less than $\bar{y}$ are defined as "negative". Then the successive elements with the same plus-minus sign constitute a succession. The number of the elements in a succession should be no less than *m*, of which the value is determined by the sampling frequency. The successions with positive

elements are called “positive succession” while those with negative elements are called “negative succession”.

a) Current data trend

If the last succession of a monitoring series is positive, the series currently has an upward trend; if it is a negative succession, the series currently has a downward trend.

b) Overall data trend

In a monitoring series, if the number of the positive successions is greater than that of the negative successions, the series has an overall upward trend; if the number of the positive successions is less than that of the negative successions, the series has a downward trend.

c) Trend recognition

If the current data trend contradicts the overall data trend, the present monitoring data are judged as abnormal; otherwise, the present monitoring data are normal.

(2) The extreme value recognition method identifies abnormalities based on the comparison of present data and the extreme values in the history. When the value of present monitoring data is greater (or less) than the maximum (or minimum) value in the history, the present value can be judged as abnormal.

(3) The neural network model method identifies abnormalities by comparing the measured value with the predicted value and examining to what extent these two

values can match. To predict the future monitoring data, neural network models are established using the monitoring time series, which can be described by Eq. (1).

$$y(t) = f(y(t-1), \ldots, y(t-d), x_1(t), \ldots, x_n(t)) \qquad \text{Eq.(1)}$$

Where, d is the number of delays, which determines the number of historical data points used in the model; y is the monitoring index; t is the sampling time; x_1, …, x_n are the effective factors. In terms of monitoring index such as crack and strain, the effective factors include internal water pressure, external water pressure, and settlement. By changing the number of neurons of the hidden layer, the number of delays, and the transfer function, the artificial neural network (ANN) model is optimized to achieve the required precision.

After a suitable model is obtained, the abnormal data can be identified with the following method (as described by Eq. (2)):

$$\begin{cases} |y_i - \hat{y}_i| \le bS, & \text{normal;} \\ |y_i - \hat{y}_i| > bS, & \text{abnormal.} \end{cases} \qquad \text{Eq. (2)}$$

Where, y_i is the measured value while $\hat{y}_i$ is the predictive value by the model; S is the standardized residual of the ANN model; b is the control parameter, which can determined based on the requirement of the actual project, and is recommended to be set as 2~3.The established models are only suitable for specific operation conditions (e.g. evacuation, normal operation, and extreme working condition). As a result, the ANN model should be retrained when the operation condition is changed.

(4) The monitoring index assessment method identifies abnormalities based on the comparison of the measured value and the predefined bounds. Based on empirical experience, the value of a monitoring index is required to be within $\left[y_{\text{low}}, y_{\text{up}}\right]$. If the present measured value is within this bound, then it is judged as normal; otherwise, the measured value is judged as abnormal.

As illustrated in Figure 4, a structure safety assessment system is developed. This system consists of two layers. In the first layer, risk level of a measuring point is evaluated based on the assessment results of the aforementioned four abnormality recognition methods (see criteria A on the left side of Table 1). In the second layer, structure safety of a pipeline segment is evaluated based on the risk levels of all the measuring points in that pipeline segment (see criteria B on the right side of Table 1). If the pipeline safety assessment reaches "yellow" level, alarms will be issued by the warning issuance module of SAWS.

5.3. SAWS

SAWS consists of two modules, i.e. warning issuance module and numerical simulation module. The warning issuance module provides an interface to manage the phone numbers and email accounts of all the participants involved in the project. When warnings are issued via phone messages, the subsequent procedures will be followed. First, service is called through the application programming interface (API) provided by the message service provider to submit request. After the service provider receives the request, the warning messages are then sent to the mobile phones of related personnel through telecommunication operators.

Numerical simulation module is developed based on the ABAQUS finite element (FE) analysis software. A 3D FE model of PCCP (the main structure of the project) is built according to a typical cross section (see Figure 5). In the established model, Mohr-Coulomb model, plastic damage model, and 3D linear elastic model are respectively used to simulate soils (including foundation layer, cushion layer, and backfill soils), tube core concrete and mortar layer, and steel cylinder and steel bars. In order to realistically simulate the present condition of PCCP, the load information (internal and external water pressure) reflected by the monitoring data and the material mechanical properties are mapped into the FE model after considering the time-varying effects. To this end, all the elements are classified according to material types to make it convenient to modify material parameters based on the established degradation model of material properties. The PCCP FE model needs to be uploaded to the database in advance, and C#.NET and Python language are used to map the real-time material parameters and load information to the elements.

5.4. 3DMS

Safety monitoring in the project requires multi-source information including monitoring data, inspection photos, and warning messages. This rich information needs to be embedded in a spatial context to provide meaningful guidance for the pipeline operation. 3DMS integrates 3D models, aerial photos, street view, and other spatial data to construct a 3D virtual scene for the water supply project, with which the safety monitoring information is dynamically coupled. This integrated system realizes the 3D visualization management of safety monitoring and makes it possible for engineers to analyze in-situ environments online.

5.4.1. Integration of multi-source spatial information and cross-platform retrieval of street view

Figure 6 illustrates the integration of various elements on a 3D GIS platform to construct a 3D virtual scene. First, the aerial photos are overlaid with Digital Elevation Model (DEM) to build the ground surface model for the project site. Second, the vector data including the transportation network and typical landmarks are overlaid with the aerial photos to indicate the geographical locations. Third, the 3D models (e.g. pipelines, monitoring station, and monitoring instruments) are exported from 3D Max and imported to the 3D GIS platform using the WGS-84 coordinate system. The layer of warning symbol (exclamation mark with different color to indicate different level of risk) is above the monitoring instruments (listed in the bottom right table in Figure 6) to indicate the abnormal positions along a pipeline segment. The street view along the pipeline segment is published through a third-party software. Clicking the video symbol located above the pipeline will provide users access to the street view, thus realizing the interaction and linkage between the street view and the 3D virtual scene. All the elements are integrated on the virtual globe that is defined on the platform.

In this project, data collection and publication of street view are accomplished by the third party. Before data collection, a route is designed according to general layout of the project. Then, along the designed route, photos of each station are captured by professionals using specialized collecting devices. The integration of 3D GIS platform and the street view platform needs to accomplish the following functionalities: (1) implant the street view into the 3D GIS platform, integrating the virtual scene of pipeline safety monitoring with street view in one screen; (2) retrieve the street view at the indicated position by evoking the associated function in the 3D GIS platform; (3) automatically roam in the virtual 3D scene by switching from the street view.

Both the street view platform and the 3D GIS platform adopt the technological framework of Web. The user interface and the specific logic are separate, and they provide Javascript API for secondary development. Hence, the independence of the data layer and application layer are preserved in the integration (as shown in Figure 7). The open-source HTML page is coded using Document Object Model (DOM) to implant the street view in the 3D GIS platform page through the HTML <iframe> label. In addition, the data communication is also realized between parent and child pages. When users click a certain feature point in the 3D scene, the click event will evoke the function to obtain the coordinates of that point. The obtained coordinates, as a parameter, will then be input to a specific function provided by the API of the street view platform to retrieve the street view at the indicated point. Using the same method, the switching from street view to 3D virtual scene can be realized.

5.4.2. Dynamic integration of safety monitoring information

To manage the safety monitoring information, SQL Server is adopted as the database platform. The photos and 3D models are stored in a file format, while the database only stores the file path. Figure 8 presents some of the database tables and their connections. The original monitoring data, in-situ photos, and warning messages are all linked to the instrument models by the instrument ID (Instrument_ID), and subsequently linked to the coordinate information. All the above safety monitoring information can be regarded as the attribute data of the instrument models, thus establishing the connection to spatial coordinate data. As a result, all of the safety monitoring information can be spatially located in the 3D virtual scene.

6. System Application

The developed system has been operated since Dec. 2015. In normal operation, monitoring data is updated via the developed interface at 6 a.m. every day. Then, the updated data is automatically analyzed. Up to now, the safety assessment results were mostly green or blue, implying that the operation of pipeline was in normal condition. From January 17 to 19, 2016, the system issued three warnings. The highest warning level was red (as shown in Figure 9(a)). Upon the receipt of the warnings, 3DMS was used to locate the warning position (seen in Figure 9(b)). Through the street view interactive browsing, surrounding environment of one of the warning positions was analyzed online. That position has a wide landscape and is close to the main road and inspection manhole (as shown in Figure 9(c)). All these factors are in favor of the execution of on-site inspection and restoration.

Given that the duration of warning issuance coincided with that of trial operation, it was assumed that the alarms were caused by the sharp rise of internal water pressure as a result of diverting water. To verify this assumption and assess the pipeline safety condition during trial operation, decision-support functions of the system were used to conduct analysis. Figure 10(a) shows that the listed three monitoring points of internal water pressure had the similar trends. There were two peaks from Jan.18, 8:00 to 20:00 and from Jan. 19 8:00 to 20:00, which corresponded to the actual period of diverting water. Figure 10(b) shows the water head along the pipeline. There are 4 lines in the diagram. The max head and the min head were respectively generated according to the maximum and the minimum of all the water pressure monitoring points along the pipeline on that day. The long-term head and the short-term head respectively indicate the theoretical water head under long-term supply flow and short-term supply flow. As can be seen from Figure 10(b), the water pressure along the pipeline corresponded to the theoretical values, indicating that the operation of the pipeline after diverting water was in a normal condition. Numerical simulation module of SAWS was used to evaluate the stress during the trial operation. Figure 10(c) presents some numerical simulation results. The unit of the stress cloud image is Pa. The loads on the water pipeline were mainly compressive stress. The largest compressive and tensile stress satisfied the requirement of PCCP pipeline.

Based on the analyses, it was confirmed that the issued warnings were caused by the sharp rise of internal water pressure as a result of diverting water. The analysis results of water head and numerical simulation demonstrated the good operation condition of the pipelines. Consequently, the warnings were canceled by the competent department.

7. Results analysis

7.1. Warning analysis

To validate the efficacy of the system, a survey was conducted to examine whether the warnings issued by the system can reflect the realistic pipeline conditions. By in-situ investigations, the reasons of warnings were investigated and then compared with the results of system assessment (see Table 2). As listed in Table 2, the warnings can be divided into three categories based on their inducements, i.e. warnings induced by operation adjustment, warnings induced by instrument failure, and warnings induced by structural issues. The frequencies and typical cases for each type of the warnings have also been presented in Table 2.

From Table 2, it was found that:

(1) The system can identify various kinds of data abnormalities induced by different factors (e.g. operation adjustment, instrument failure, and structural issues), and issue the relevant levels of warnings.

(2) Up to now, the most frequent warnings were those induced by operation adjustment, which probably were due to the frequent trial test in the early stage of operation.

(3) Different kinds of warnings are characterized by different patterns: warnings induced by the operation adjustment usually occur on several pipeline segments at the same time; warnings induced by instrument failure occur on individual monitoring points, and the corresponding risk levels are relatively low; warnings induced by structural issues usually occur on several monitoring points at the same time, and the abnormal points are generally located at the adjacent monitoring sections.

7.2. Precision of neural network model

In this section, joint meter JT-1-J1 and strain gauge JT-4-SP1 were taken as examples to demonstrate the ANN training process and validate the precision of the model. As illustrated by Figure 11, the inputs of the model include the crack (or strain) during the last *d* sampling periods, present internal water pressure, external water pressure, and settlement. The output is the present crack (or strain). Figure 12 shows the data graphs of JT-1-J1, JT-4-SP1, and the corresponding external loads between Dec. /1st/2016 and Jan. /31st/2017.

The data between Dec. /1st/2016 and Jan. /20th/2017 (normal operation with the flow of 7m^3/s) was used as training samples (totally 51 groups). The network parameters (*d*, the number of neurons of the hidden layer, and the transfer function) are adjusted to optimize the model. For JT-1-J1, when *d*, the number of neurons of the hidden layer, and the transfer function are respectively set as 2, 12, and tansig, the optimum model is obtained (with the Mean Squared Error (MSE) of 7.22×10^{-4}), as shown on the left side of Figure 13 (a). For JT-1-J1, the optimal parameter values are 3, 10 and tansig, upon which the MSE of the model is 1.52×10^{-3}, as shown on the left side of Figure 13 (b).

The data between Jan. /21st/2017 and Jan. /31st/2017 (working condition ditto) was used as testing samples (totally 11 groups). The results are presented on the right side of Figure 13. As shown by Figure 13, the predictive values match well with the measured values. The maximum relative errors of prediction for JT-1-J1 and JT-4-SP1 are both less than 1.0%, which indicates a high accuracy of prediction.

8. Conclusions and Future Works

Current practice for safety management in water diversion projects suffers from both technical and managerial limitations. To address the limitations, this study proposes to adopt 3D GIS, street view, data mining and numerical simulation, to integrate data collection, data analysis, warning issuance and decision-making support into a holistic framework for safety management of water diversion projects. This proposed framework streamlines the whole management process and improves the efficiency of emergency response. To implement the proposed framework, a system prototype was developed and implemented in a water supply project located in Tianjin, China. The system operates well up to now, which can automatically evaluate the pipeline safety condition and issue warning messages. The system also provides a decision-support platform with comprehensive functions after a warning is issued. The application study suggests that the prototype system has achieved the expected requirements, thus validating the efficacy of the proposed framework.

The long-term performance of this developed system under different working conditions needs further observation. Moreover, although the system has the visualization capability to locate warning position and analyze in-situ environment, it is still difficult for engineers to determine the location of potential safety issues during on-site inspection. In future works, the augmented reality (AR) technology is expected to address the limitation. Using AR in mobile devices or using the specialized device such as Hololens, the virtual scene of pipeline layout and the safety assessment results can be embedded into the real environment, thus helping the engineers to determine the alarm position.

Acknowledgements

This research was supported by the Foundation for Innovative Research Groups of the National Natural Science Foundation of China (No. 51321065), and the National Natural Science Foundation of China (No. 51479132, No. 51679164).

References

[1] Bureau of South to North Water Transfer of Planning, Designing and Management, Ministry of Water Resources (BSNWTPDM, MWR), Inter-basin water transfer and regional water resources allocation, 2012, Beijing, China: China Water & Power Press (in Chinese).

[2] A.M. Sadeghioon, R. Walton, D. Chapman, et al., Design and Development of a Nonintrusive Pressure Measurement System for Pipeline Monitoring, Journal of Pipeline Systems Engineering and Practice 5 (3) (2014), https://doi.org/10.1061/(asce)ps.1949-1204.0000169.

[3] M. Pour-Ghaz, J. Kim, S.S. Nadukuru, et al., Using electrical, magnetic and acoustic sensors to detect damage in segmental concrete pipes subjected to permanent ground displacement, Cement & Concrete Composites 33 (7) (2011) 749-762, https://doi.org/10.1016/j.cemconcomp.2011.04.004.

[4] M. Eybpoosh, M. Berges,H.Y. Noh, Sparse representation of ultrasonic guided-waves for robust damage detection in pipelines under varying environmental and operational conditions, Structural Control & Health Monitoring 23 (2) (2016) 369-391, https://doi.org/10.1002/stc.1776.

[5] T. Sivanadyan,A. Sayeed, Active wireless sensing in multipath environments, 2007 IEEE/SP 14th WorkShoP on Statistical Signal Processing, SSP 2007, August 26, 2007 - August 29, 2007, 2007, Madison, WI, United states: Inst. of Elec. and Elec. Eng. Computer Society, https://doi.org/10.1109/ssp.2007.4301284.

[6] J.S. Pei, C. Kapoor, T.L. Graves-Abe, et al., An experimental investigation of the data delivery performance of a wireless sensing unit designed for structural health monitoring, Structural Control & Health Monitoring 15 (4) (2008) 471-504, https://doi.org/10.1002/stc.205.

[7] S. Bharti,K.K. Pattanaik, Gravitational outlier detection for wireless sensor networks, International Journal of Communication Systems 29 (13) (2016) 2015-2027, https://doi.org/10.1002/dac.3155.

[8] T.C. Beckham, Software applications for monitoring instrumentation data, Proceedings of Geotechnical Practice in Dam Rehabilitation, April 25, 1993 - April 28, 1993, 1993, Raleigh, NC, USA: Publ by ASCE. Available from: http://cedb.asce.org/CEDBsearch/record.jsp?dockey=0081202.

[9] Geokon Inc., Pipeline Monitoring Projects. Available from: http://www.geokon.com/Pipelines.

[10] L. Peyras, P. Royet,D. Boissier, Dam ageing diagnosis and risk analysis: Development of methods to support expert judgment, Canadian Geotechnical Journal 43 (2) (2006) 169-186, https://doi.org/10.1139/t05-096.

[11] G.Q. Yu, Z.L. Wang, Z.Z. Tian, et al., Implementation of Data Mining in Sluice Safety Monitoring, Frontiers of Green Building, Materials and Civil Engineering, Pts 1-8 71-78 (2011) 4329-4332, https://doi.org/10.4028/www.scientific.net/amm.71-78.4329.

[12] H. Fares,T. Zayed, Hierarchical Fuzzy Expert System for Risk of Failure of Water Mains, Journal of Pipeline Systems Engineering and Practice 1 (1) (2010) 53-62, https://doi.org/10.1061/(asce)ps.1949-1204.0000037.

[13] M.R. Halfawy, L. Dridi,S. Baker, Integrated Decision Support System for Optimal Renewal Planning of Sewer Networks, Journal of Computing in Civil Engineering 22 (6) (2008) 360-372, https://doi.org/10.1061/(asce)0887-3801(2008)22:6(360).

[14] H. Zhang, S. Chi, J. Yang, et al., Development of a Safety Inspection Framework on Construction Sites Using Mobile Computing, Journal of Management in Engineering 33 (3) (2017), https:// doi.org/10.1061/(asce)me.1943-5479.0000495.

[15] M.S. Zarghamee, D.W. Eggers, R. Ojdrovic, et al., Risk analysis of prestressed concrete cylinder pipe with broken wires, Proceedings of the ASCE International Conference on Pipeline Engineering and Construction, July 13, 2003 - July 16, 2003, 2003, Baltimore, MD, United states: American Society of Civil Engineers, https://doi.org/10.1061/40690(2003)81.

[16] M.S. Zarghamee, D.W. Eggers, R.P. Ojdrovic, Finite-element modeling of failure of PCCP with broken wires subjected to combined loads, Pipelines 2002 - Beneath Our Feet: Challengers and Solutions - Pipeline Division Specialty Conference, August 4, 2002 - August 7, 2002, 2002, Cleveland, OH, United states: American Society of Civil Engineers, https://doi.org/10.1061/40641(2002)66.

[17] Y.G. Diab,T. Bonierbale, A numerical modeling and a proposal for rehabilitation of PCCP's, Pipelines 2001: Advances in Pipeline Engineering and Construction, July 15, 2001 - July 18, 2001, 2004, San Diego, CA, United states: American Society of Civil Engineers, https://doi.org/10.1061/40574(2001)36.

[18] S. Villegas, X.O. Li,W. Yu, Detection of Building Structure Damage with Support Vector Machine, 2015 IEEE 12th International Conference on Networking, Sensing and Control (ICNSC) (2015) 619-624, https://doi.org/10.1109/icnsc.2015.7116109.

[19] Y. Xia, P. Zhang,Y.Q. Ni, Displacement of a Skyscraper Using Various Types of Field Monitoring Data, Structural Health Monitoring 2013, Vols 1 and 2 (2013) 1679-1685. Available from: http:// dl.handle.net/10397/56480.

[20] L.S. Li, R.J. Hansman, R. Palacios, et al., Anomaly detection via a Gaussian Mixture Model for flight operation and safety monitoring, Transportation Research Part C-Emerging Technologies 64 (2016) 45-57, https:// doi.org/10.1016/j.trc.2016.01.007.

[21] P. Royer, J. De Ridder, B. Vandenbussche, et al., Data mining spacecraft telemetry: Towards generic solutions to automatic health monitoring and status characterisation, Observatory Operations: Strategies, Processes, and Systems Vi 9910 (2016), https://doi.org/10.1117/12.2231934.

[22] X.O. Li, W. Yu,S. Villegas, Structural Health Monitoring of Building Structures With Online Data Mining Methods, Ieee Systems Journal 10 (3) (2016) 1291-1300, https://doi.org/10.1109/jsyst.2015.2481380.

[23] S. Khazaeli, A.G. Ravandi, S. Banerji, et al., The application of data mining and cloud computing techniques in data-driven models for structural health monitoring, Health Monitoring of Structural and Biological Systems 2016 9805 (2016), https://doi.org/10.1117/12.2218707.

[24] B. Salman,O. Salem, Risk Assessment of Wastewater Collection Lines Using Failure Models and Criticality Ratings, Journal of Pipeline Systems Engineering and Practice 3 (3) (2012) 68-76, https://doi.org/10.1061/(asce)ps.1949-1204.0000100.

[25] V.R. Sekar, S.K. Sinha,S.M. Welling, Web-Based and Geospatially Enabled Risk Screening Tool for Water and Wastewater Pipeline Infrastructure Systems, Journal of Pipeline Systems Engineering and Practice 4 (4) (2013), https://doi.org/10.1061/(asce)ps.1949-1204.0000139.

[26] J. Coffey, A. Oppong-Bawuah, D. Marshall, et al., Information pipeline: Enhancing pipeline management analysis using GIS at the tarrant regional water district, Pipelines 2007: Advances and Experiences with Trenchless Pipeline Projects, July 8, 2007 - July 11, 2007, 2007, Boston, MA, United states: American Society of Civil Engineers, https://doi.org/10.1061/40934(252)111.

[27] R. Liu,R.R.A. Issa, 3D Visualization of Sub-surface Pipelines in Connection with the Building Utilities: Integrating GIS and BIM for Facility Management, 2012 ASCE International Conference on Computing in Civil Engineering, 17-20 June 2012, 2012, Reston, VA, USA: American Society of Civil Engineers, https://doi.org/10.1061/9780784412343.0043.

[28] B. Wu, B. Cui,D. Zhong, Web-based 3D Visualization of Dam Safety Monitoring, Advanced Materials Research 594-597 (4) (2012) 2927-31, https://doi.org/10.4028/www.scientific.net/amr.594-597.2927.

[29] E. Deus, J.S. Silva, F.X. Catry, et al., Google Street View as an alternative method to car surveys in large-scale vegetation assessments, Environmental Monitoring and Assessment 188 (10) (2016), https://doi.org/10.1007/s10661-016-5555-1.

[30] S.J. Mooney, C.J. DiMaggio, G.S. Lovasi, et al., Use of Google Street View to Assess Environmental Contributions to Pedestrian Injury, American Journal of Public Health 106 (3) (2016) 462-469, https:// doi.org/10.2105/ajph.2015.302978.

[31] P.P. Olea,P. Mateo-Tomas, Assessing Species Habitat Using Google Street View: A Case Study of Cliff-Nesting Vultures, Plos One 8 (1) (2013), https://doi.org/10.1371/journal.pone.0054582.

[32] S.H. Oh, K.S. Lee,W.M. Jeong, Three-dimensional experiment and numerical simulation of the discharge performance of sluice passageway for tidal power plant, Renewable Energy 92 (2016) 462-473, https://doi.org/10.1016/j.renene.2016.02.023.

[33] J.Y. Chen, X.P. Liu,Q. Xu, Numerical simulation analysis of damage mode of concrete gravity dam under close-in explosion, Ksce Journal of Civil Engineering 21 (1) (2017) 397-407, https://doi. org/10.1007/s12205-016-1082-4.

[34] Geokon Inc., Manual of LogView Software. Available from: http://www.geokon.com/8001-3.

Tables

Tab. 1. Pipeline safety assessment criteria.

First layer - Abnormalities Recognition		**Second layer- Pipeline Safety Assessment**		
Risk level	**Criteria – A**	**Risk level**	**Criteria – B**	**Warning? (Y/N)**
Green	Recognized ‘normal’ by all the 4 methods	Green	With no measuring point over ‘blue’ level	N
Blue	Recognized ‘abnormal’ by 1 of the 4 methods	Blue	With 1 measuring point reaching ‘yellow’ level	N
Yellow	Recognized ‘abnormal’ by 2 of the 4 methods	Yellow	With more than 3 measuring points reaching ‘yellow’ level, or with 1 measuring point reaching ‘orange’ level	Y
Orange	Recognized ‘abnormal’ by 3 of the 4 methods	Orange	With more than 3 measuring points reaching ‘orange’ level, or with 1 measuring point reaching ‘red’ level	Y
Red	Recognized ‘abnormal’ by all of the 4 methods	Red	With more than 3 measuring points reaching ‘red’ level	Y

Tab. 2. Warnings issued during the system application.

Type	**Number of times**	**Typical case**								
		Time and location	Risk level of pipeline	Monitoring point	Method 1#	Method 2#	Method 3#	Method 4#	Risk level of Monitoring point	Reason description
Warnings induced by operation adjustment	7	01/18/2016 Segment. JS	Red	JS-1-J1	√	×	×	√	Yellow	Sharp rise of internal water pressure during trial operation
				JS-2-J3	×	×	×	√	Orange	
				JS-3-SP1	×	×	×	×	Red	
				JS-3-SP2	×	×	×	×	Red	
				JS-3-PI	×	×	×	×	Red	
		01/18/2016 Segment. F1	Orange	F1-1-J1	√	×	×	√	Yellow	Sharp rise of internal water pressure during trial operation
				F1-2-PI	×	×	×	×	Red	
				F1-3-J3	×	×	×	√	Orange	
Warnings induced by instrument failure	3	03/20/2016 Segment. F1	Yellow	F1-1-J1	√	×	×	×	Orange	Instrument fault with joint meter F1-1-J1
				F1-1-J2	√	√	√	√	Green	
				F1-2-P	√	√	√	√	Green	
Warnings induced by structural issues	2	12/11/2016 Segment. JG	Orange	JG-1-J1	√	×	×	×	Orange	Leakage in the joint between steel pipe and PCCP
				JG-1-J2	√	×	×	√	Yellow	
				JG-2-J3	×	×	×	×	Red	
				JG-2-J4	×	×	×	√	Orange	
				JG-2-P1	√	×	×	√	Yellow	
		03/05/2017 Segment. JL	Orange	JL-5-J5	√	×	×	×	Orange	Leakage in the joint between steel pipe and PCCP
				JL-5-J6	√	√	×	√	Blue	
				JL-5-P3	×	×	×	√	Orange	
				JL-6-J7	×	×	×	√	Orange	
				JL-6-J8	√	×	×	√	Yellow	

Notes: 1. Method 1# ~ Method 4# separately represent the aforementioned 4 abnormalities recognition methods (i.e. trend recognition, extreme value recognition, neural network model, and monitoring index assessment).

2. The symbol "√" refers to normal while "×" refers to abnormal; the risk level is obtained according to the criteria in Table 1.

3. The monitoring points can be described as "segment - section - instrument", and each type of the instruments is denoted by certain characters: joint meter - J, strain gauge - SP, external water pressure meter - P, internal water pressure meter - PI.

Figures

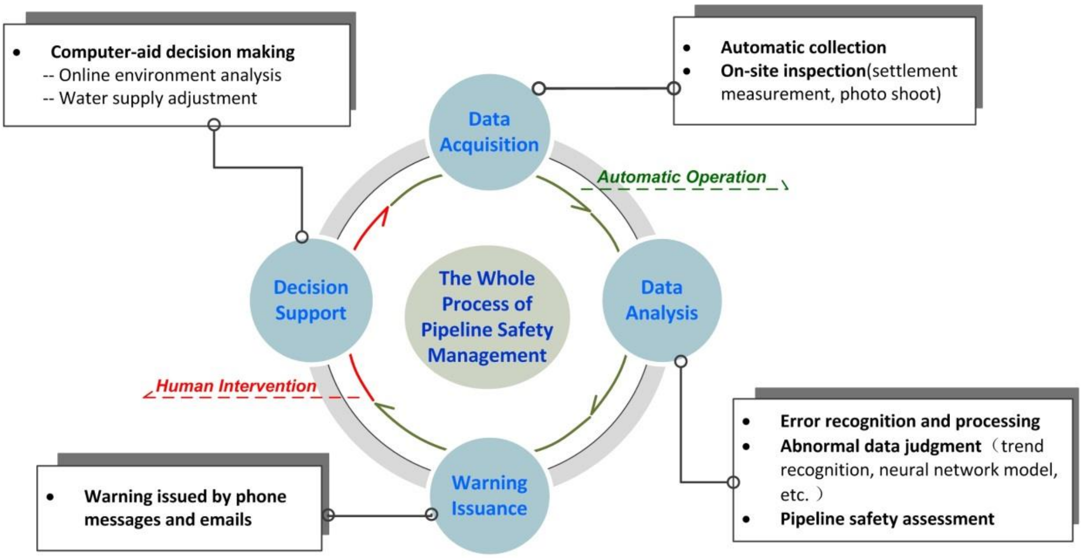


Fig. 1. Flowchart of whole-process pipeline safety management.

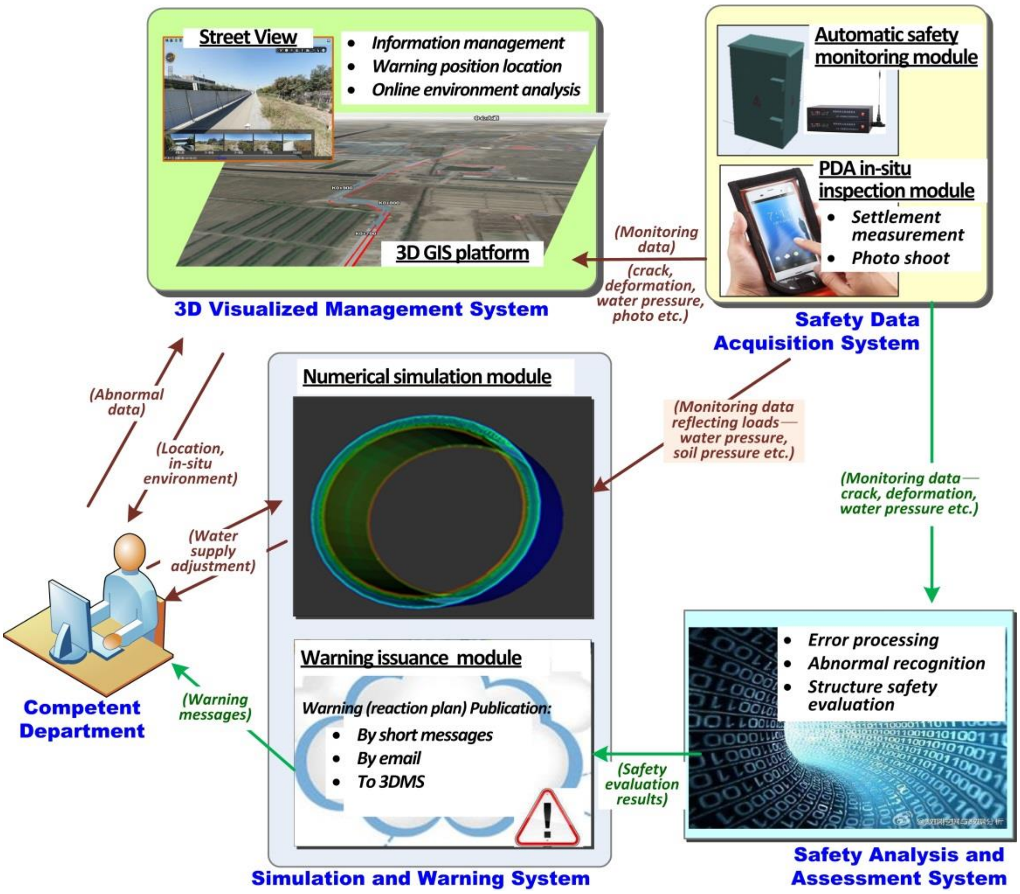


Fig. 2. Architecture of the proposed framework.

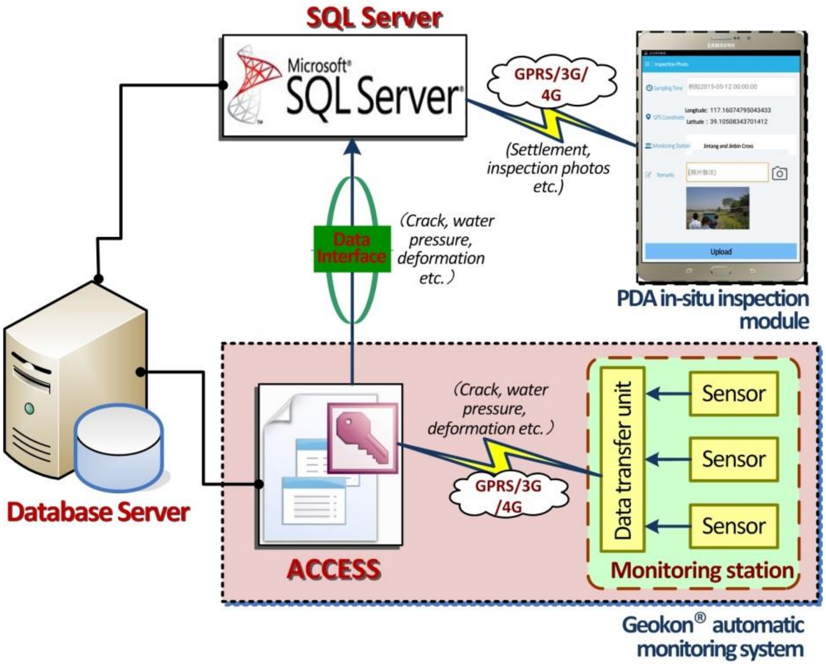


Fig. 3. Technical route of safety monitoring data integration.

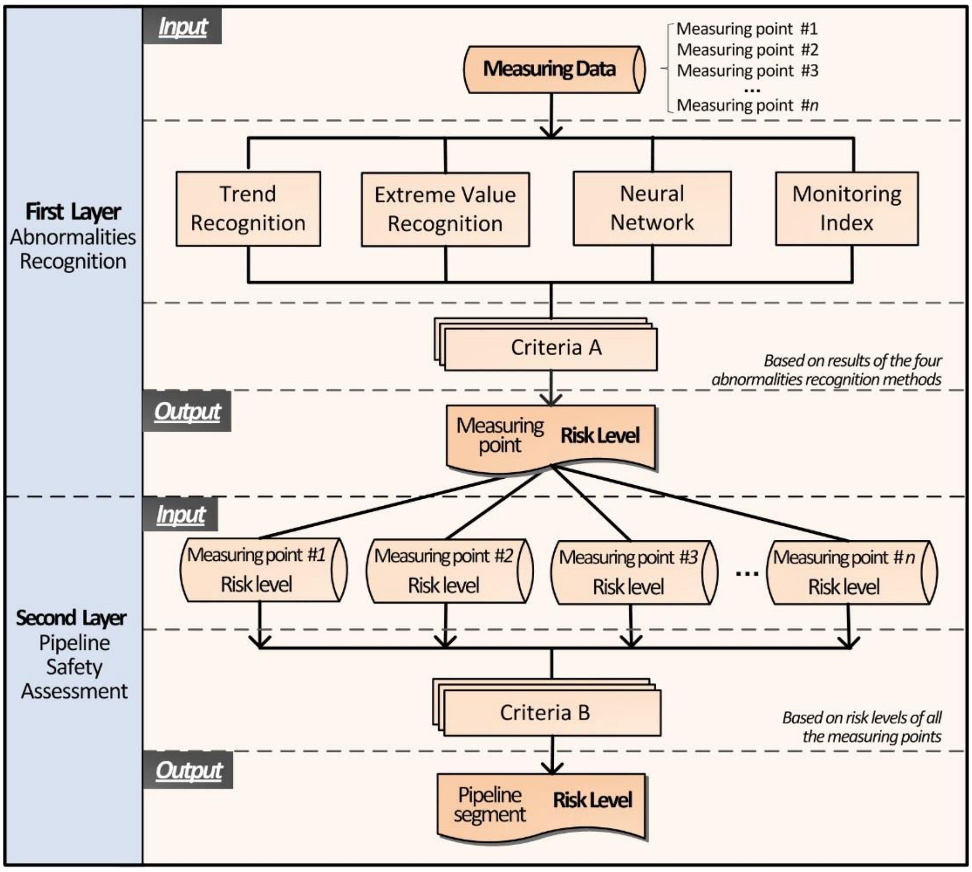


Fig. 4. Safety assessment system of water diversion projects.

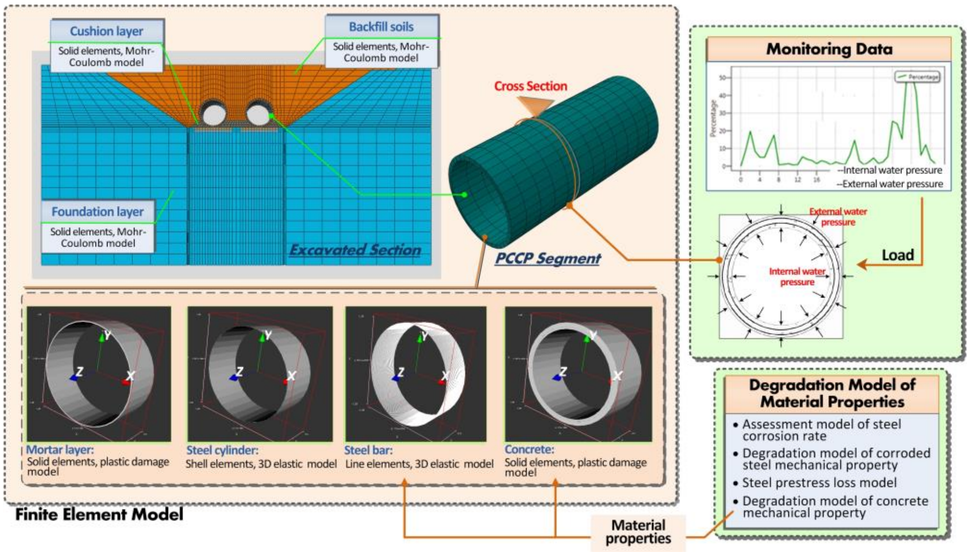


Fig. 5. 3D finite element model of PCCP.

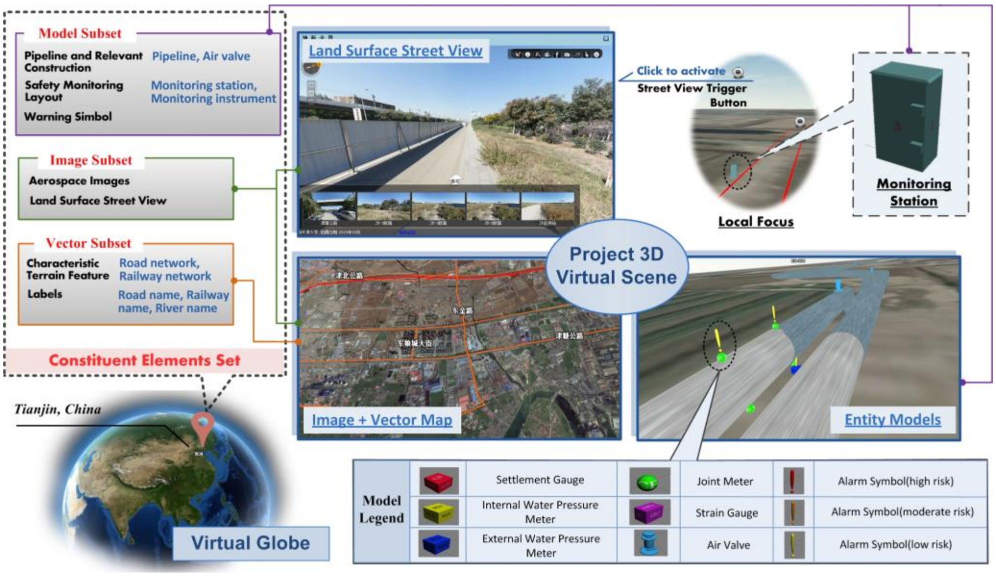


Fig. 6. Organization of multi-source information for safety monitoring.

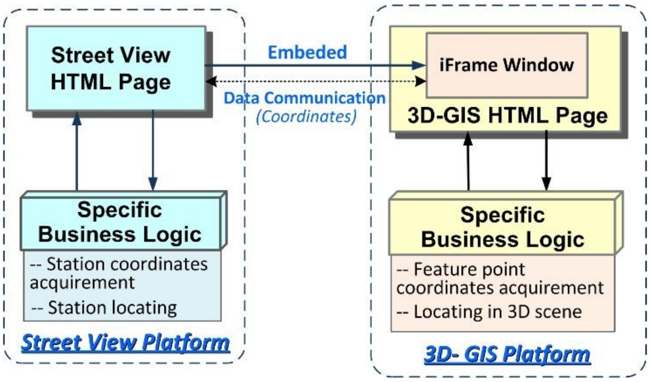
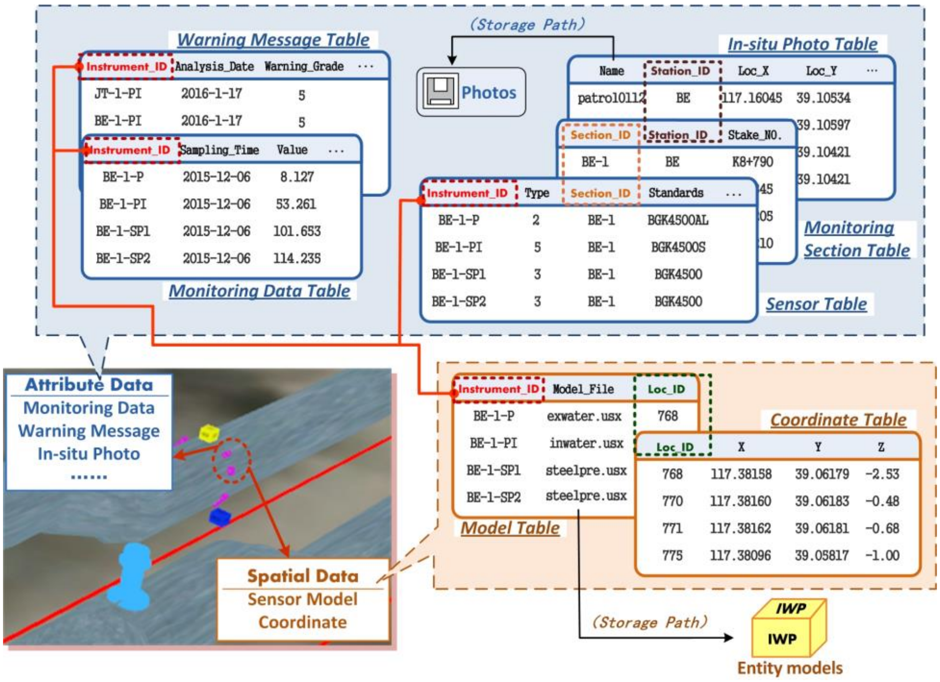


Fig. 7. Cross platform integration of street view.



Warning Message Table

Instrument_ID	Analysis_Date	Warning_Grade	…
JT-1-PI	2016-1-17	5	
BE-1-PI	2016-1-17	5	

Monitoring Data Table

Instrument_ID	Sampling_Time	Value	…
BE-1-P	2015-12-06	8.127	
BE-1-PI	2015-12-06	53.261	
BE-1-SP1	2015-12-06	101.653	
BE-1-SP2	2015-12-06	114.235	

In-situ Photo Table

Name	Station_ID	Loc_X	Loc_Y	…
patrol0112	BE	117.16045	39.10534	
			39.10597	
			39.10421	
			39.10421	

Monitoring Section Table

Section_ID	Station_ID	Stake_NO.
BE-1	BE	K8+790
		45
		05
		10

Sensor Table

Instrument_ID	Type	Section_ID	Standards	…
BE-1-P	2	BE-1	BGK4500AL	
BE-1-PI	5	BE-1	BGK4500S	
BE-1-SP1	3	BE-1	BGK4500	
BE-1-SP2	3	BE-1	BGK4500	

Model Table

Instrument_ID	Model_File	Loc_ID
BE-1-P	exwater.usx	768
BE-1-PI	inwater.usx	
BE-1-SP1	steelpre.usx	
BE-1-SP2	steelpre.usx	

Coordinate Table

Loc_ID	X	Y	Z
768	117.38158	39.06179	-2.53
770	117.38160	39.06183	-0.48
771	117.38162	39.06181	-0.68
775	117.38096	39.05817	-1.00

Fig. 8. Diagram of dynamic integration of safety monitoring information.

[Safety Alarm] Jan. 17th, 2016. Abnormalities were detected. Highest level: RED. Please pay attention !!

[Safety Alarm] Jan. 18th, 2016. Abnormalities were detected. Highest level: RED. Please pay attention !!

1/18/2016 Abnormalities were detected, please check detailed information!

Analysis Time 2016/1/18 18:00:00

Instrument ID	Warning Level
JT-1-J1	YELLOW ALERT
JT-1-J2	YELLOW ALERT
JT-2-J3	ORANGE ALERT
JT-2-J4	ORANGE ALERT
[illegible]	RED ALERT
JT-4-SP1	YELLOW ALERT
JT-4-SP2	YELLOW ALERT
JT-4-SP3	YELLOW ALERT
JT-4-SP4	YELLOW ALERT
JT-4-SP5	YELLOW ALERT
JT-4-SP6	YELLOW ALERT
JT-4-SP7	YELLOW ALERT
JT-4-SP8	YELLOW ALERT
JB-1-J1	ORANGE ALERT
JB-1-J2	ORANGE ALERT

Fig. 9. (a) Warning massage on mobile phone; (b) Warning issuance on 3D GIS platform; (c) Surrounding environment of one warning position.

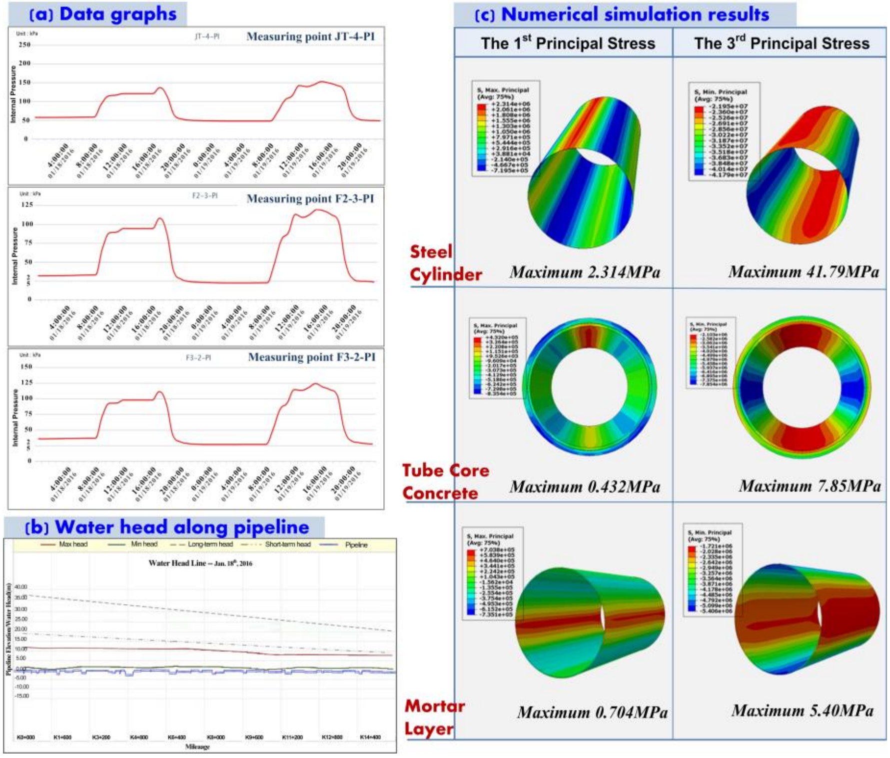


Fig. 10. Safety analysis during trial operation.

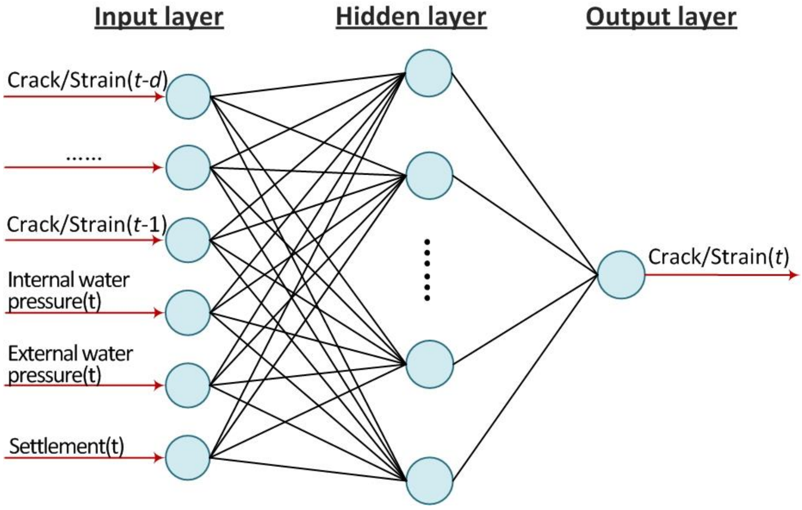


Fig. 11. ANN models for JT-1-J1 and JT-4-SP1.

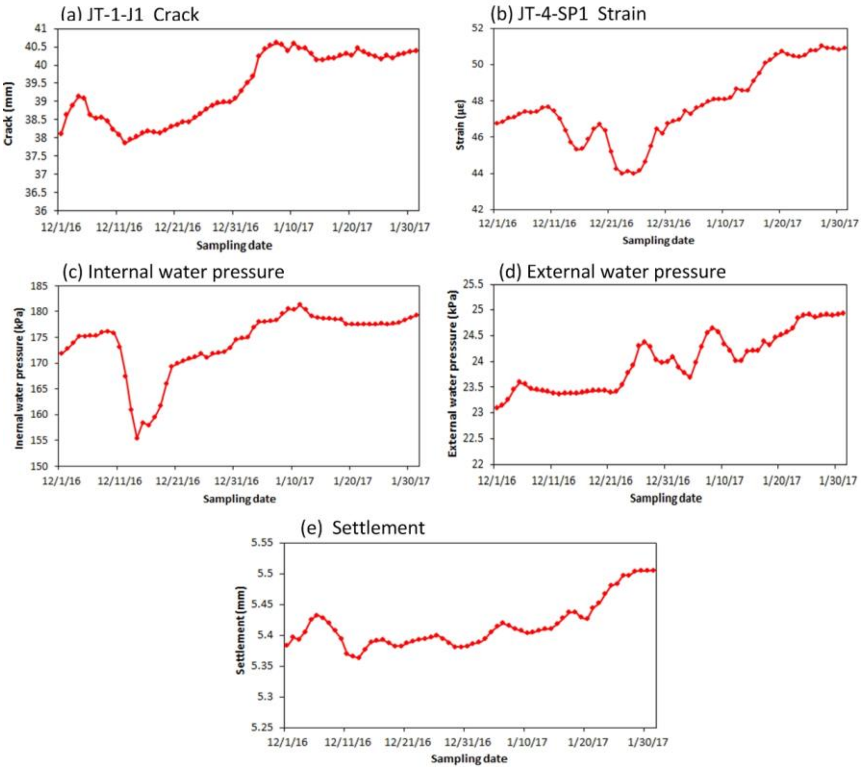


Fig. 12. Data graphs of selected monitoring points and external loads.

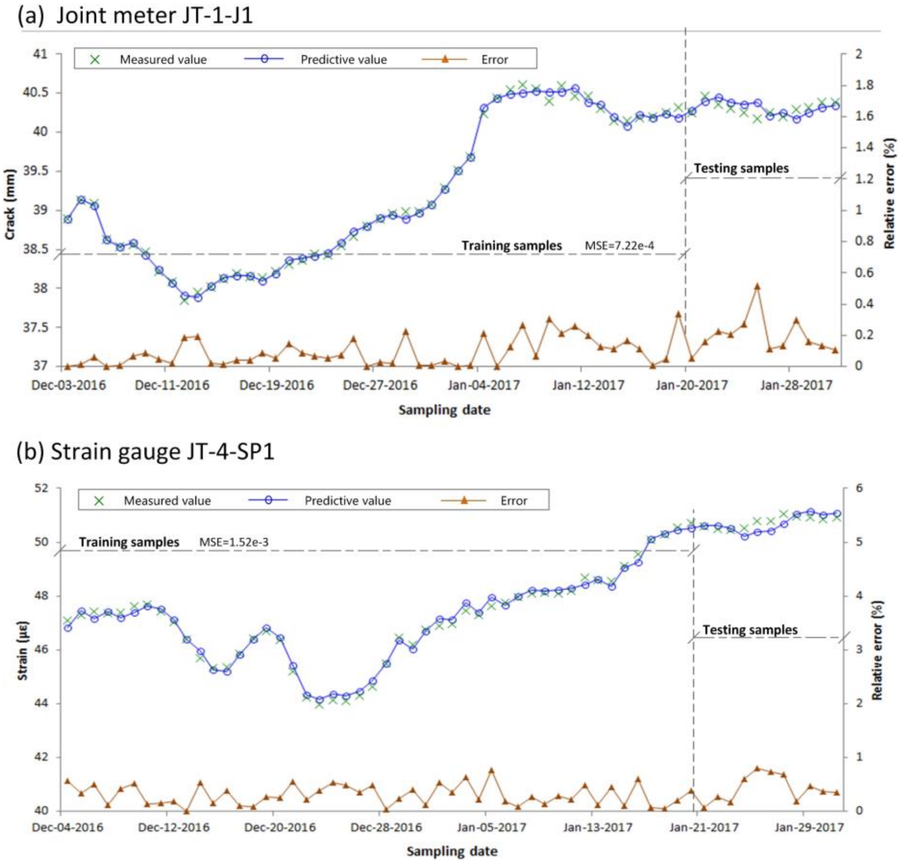


Fig. 13. Precision analysis of the established neural network model.