Establishment of a large-diameter pipeline failure risk matrix in water distribution systems in Taiwan

Kochin Huang, Paul Chuo, Kim-loong Lin, Mengsyu Yu and Chihpin Huang

ABSTRACT

The bursting of large-diameter water pipelines in distribution systems will lead to industrial, economic, and public safety impacts. Therefore, multi-criteria analysis (MCA) was applied in this study, which utilizes a series of quantifiable parameters to establish the mathematical method of a risk model. The risk matrix of a pipeline was defined as the multiple of the probability of pipeline failure and potential consequences of pipeline failure. By combining the GIS (geographic information system), each evaluation unit was assigned to different risk levels. The large-diameter (above 800 mm) pipeline length statistic for various risk evaluation units of Taiwan Water Corporation reveals the length of high risk is 171 km (7.7%), secondary high risk 574.6 km (25.8%), middle risk 714.3 km (32%), low risk 701.5 km (31.5%), and the unranked length is 67.8 km (3.0%). Finally, the detection frequencies were classified as high risk with a term check of every five years, sub-high risk with planned check every five to ten years, medium risk with checking/monitoring if needed, and low risk with quick repair and no need to take measurements and monitoring. Therefore, we can significantly lower the probability of bursting for large-diameter pipelines in the water distribution system.

Key words | multi-criteria analysis, pipe failure model, risk matrix, water distribution system

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INTRODUCTION

Since 2000, the average number of water pipe breaks every day have been around 700 in Canada, while the annual cost of pipeline repair in the United States is 10 billion dollars more than that in Canada (Kabir *et al.* 2015b). Cities in Europe spend about 1 billion euros every year to repair water pipelines, and with pipe aging in the next few decades, the costs are expected to increase constantly (Rostum 2000). Cities and townships in North America are encountering the issues of pipeline infrastructure aging and poor management, which may cause serious problems in politics, finance, and economics (Jones 2012). Hence, it is important to rehabilitate pipelines at the optimal time in order to lower infrastructure risks.

Countries around the world have been aggressively developing pipeline maintenance approaches involving the failure prediction model and risk management in the field of decision support systems (Moglia *et al.* 2006). Traditional technologies of using failure factors (e.g., pipes and hydraulic indicators) combined with a Bayesian model would contribute to getting the correct strategy for maintenance or renewal (Dridi *et al.* 2005; Economou *et al.* 2012; Morosini *et al.* 2014; Kabir *et al.* 2015a, 2015b). Further, using fault prediction and multi-criteria decision analysis (Malinowska 2017), PARMS (Pipeline Asset and Risk Management System), water supply pipeline update decision system (Karimian 2015; Kutyłowska 2017), artificial neural network modules such as Road (ANN) (Xu *et al.* 2013), and evolutionary polynomial regression (Gaewski & Blaha 2007; Xu *et al.* 2013) would contribute to decision-making of pipeline replacement priorities. Currently, the most commonly used are the real-time model combining with Supervisory and Data

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Collection System (SCADA) (Boulos *et al.* 2014), Instant Wisdom Water Network Decision Support System (SWNDSS) (Li *et al.* 2011), geographic information system, and regional measurement management information District Metering Area to establish a large ring network for predicting leakage points (Du *et al.* 2012). In addition, some studies used forensic transients to analyze pipeline faults, including water pressure and power outage conditions. If the final inspection was not completed correctly, the accuracy of the numerical method is meaningless; therefore, it must be verified whether the fault diagnosis is correctly described (Ivetic 2004; Pozos-Estrada *et al.* 2012, 2016).

Although the software models mentioned above can be used to predict pipeline failure through various statistical analyses, they do not take the impact caused by pipeline failure into account. Once a large-diameter pipeline bursts, it usually affects a large area, and accordingly, the risk of consumers must be taken into consideration (Moglia *et al.* 2006; Gaewski & Blaha 2007). According to the statistics from Taiwan Water Corporation (TWC) in 2018, the length of water distribution pipeline above 800 mm (inclusive) is 2,234,872 meters, which is approximately 3.63% of the total pipeline length of 61,457,604 meters. If a large-diameter pipeline breaks, it may result in not only vast water leakage causing water shortage to a great number of residents, but also industrial economic and public safety impacts. The existing statistics software is either complex or with various factors, and has limitations within it, and therefore no failure risk model for water distribution pipelines above 800 mm has been established yet. Inasmuch for this reason, in this study we adopted the multi-criteria analysis (MCA) method (Dodgson *et al.* 2009), as well as the existing data to build a risk matrix, which can be used to predict the potential risks of pipeline failures effectively, and provide a reference for large pipeline (above 800 mm) renewal scheme.

METHODS

We collected the data from 12 districts of Taiwan Water Corporation (TWC) in this research. These were classified into four major levels, including design, assets, environment, and operation.

1. Design level: Three impact factors are considered, including: the design data of pressurization station, water purification field, and distribution pool; planning result for each area; and pipeline network mode.
2. Assets level: Nine impact factors are considered, including: GIS (geographic information system) mapping; regular maintenance data of water distribution pipeline; lining information of pipeline for all grades; pipeline renewal information; assets management system; repairing management system; water meter recording data from computer; statistics of water sales over the years; and, historical contract prices.
3. Environment level: one impact factor, which is traffic flow.
4. Operation level: Five impact factors are considered, including: the record of water pressure and quality; SCADA (supervisory control and data acquisition) monitoring data; automatic meter reading system; the existing meter reading manners in each district; and, water distribution system and other operation modes of water supply facilities.

Considering numerous failure impact factors in this study, MCA was adopted in this study. It utilizes a series of quantifiable parameters to evaluate the risk of each unit, and is also a computing mechanism for risk model. The advantages of applying it on pipeline assessment are as follows:

1. The appropriate factors can be determined after the needs are fully discussed by parties.
2. The weight of each factor can be adjusted according to the correctness, completeness, or importance of data.
3. The results of pipeline detection can be brought in as a new factor for future analysis.

The risk of the water pipeline (R) is composed of the probability of failure (L) and the consequence of failure (C). The value of L and C can be counted according to the features of the pipeline, and each is normalized between 0 and 100. By multiplying L and C, the risk score (R), which is adopted as the baseline for the risk ranking of the target pipeline, can be obtained. The formula is as follows:

$$R = L \times C/100$$

If the failure probability of the pipeline is zero (assuming the pipeline would never burst), the total risk will still be zero regardless of the high effect of failure (numerous affected users, long repair time, high cost); similarly, if the consequence of failure (C) is zero, despite the extraordinarily high probability of failure (poor material, high pipe age, high water pressure, frequent road traffic), the total risk is still zero.

Factor selecting

The pipeline condition assessment means collecting data or information in direct or indirect ways and analyzing them to verify the structure, water quality, and hydraulic condition of pipelines currently or in the future, as well as taking the environment factors of topography or geology into consideration. In other words, it stands for the degree affected to the risk of water supply equipment failure. Therefore, by reference to the international pipeline risk assessment practices, the pipeline risk level was defined as the multiple of the following two items, the probability of pipeline failure and the potential consequences of pipeline failure.

The probability of pipeline failure

The probability of pipeline failure refers to the occurrence of probability that the pipeline reduces supply or there is a total loss of the water supply capacity resulting from the structural damage to the pipeline itself or external forces. According to the US Environmental Protection Agency's (USEPA) 2012 issue of Condition Assessment Technologies for Water Transmission and Distribution Systems, two indicators were adopted for evaluating the conditions of pipeline, namely, distress indicator and inferential indicator.

1. Distress indicator: Rajani *et al.* (2006) defined the distress indicator of pipelines as a physical indicator from observation or measurement during the process of pipeline aging. However, different types of pipes apply to different indicators. For example, when structural damage occurs on a metal pipeline (e.g., DIP (ductile iron pipe) or CIP (cast iron pipe), it is possible that there may be corrosion inside or outside, and through electromagnetic detection, the cavitations on the surface of the metal can be measured; if the steel wires inside a concrete pipe (e.g., PCCP (prestressed concrete cylinder pipe) or PSCP (prestressed concrete non-cylinder pipe) break to a specific extent, it is likely that the pipe may be unable to withstand water pressure and result in bursting. Consequently, the risk of concrete pipes can be evaluated through detecting the condition of internal steel breaks by the instrument.
2. Inferential indicator: When the condition of pipeline structure cannot be judged by excavation or other non-destructive testing, it can simply be evaluated through environmental conditions or operation methods. The advantages of inferential statistics are both fast and cheap, but the accuracy depends on the credibility and completeness of data sources, and if the quality of data is poor, it is necessary to redo the check by detection equipment or visual inspection.

However, comparing the detection approaches of indicators proposed by USEPA as mentioned above, as far as the distress indicator method is concerned, these data are usually obtained through excavation or non-destructive testing. In contrast, the inferential indicator method has the advantages of being accessible, fast and economical and, furthermore, only the on-site inspection work is exclusive in this research. As explained above, it is more reasonable to select the appropriate items from inferential indicators as the impact factors for evaluating the probability of pipeline failure. After obtaining the high-risk pipeline inspection results later, some other distress indicators can be added to update the evaluation results as needed.

Overall, this research of the probability of pipeline failure followed the inferential indicator approach which satisfies the features of being independent and being accessible for objective and complete data, and summarizes four factors, including the structure aspect of pipe, the operation aspect of water pressure, the environment aspect of road traffic, and the assets aspect of age, respectively.

Potential consequences of pipeline failure

In this study, the potential consequences of pipeline failure was based on the analysis of historical burst events, and summarizes the four factors which satisfy the features of:

being independent of each other; the degree of water supply impact (i.e., the number of households multiplying by repair time produces the total impact on water supply); direct and indirect impact (i.e., assets, direct and indirect revenue losses, and the damage to proximity properties); and, complete and accessible data, including number of affected households, repair time, loss of revenue, and damage of proximity properties, respectively.

Factor weighting

The correlation between factors and risks is provided by the weight and can be adjusted with the improvement of data quality, the feedback from on-site testing results, or the changes of affordable risk. Therefore, in this study, we adjusted the weights (including the completeness and confidence level) according to the real quality of available data from TWC, and verified the sensitivity (i.e., correlation) among various factors by questionnaires, illustrated as follows below.

Regarding the leak repair record system currently, in Figure 1, the rows related to the probability of pipeline failure are the pipe material and the water pressure before and after pipe bursting. Those related to potential consequences of pipeline failure are requirement reception, order dispatch, and time of beginning and completion. The proportion of filled data are indicated in Figure 1. Since the repair records are the observation results from actual repair and excavation, they belong to high confidence data and can be used as the basis for subsequent analysis; also, different weights are given according to the degree of completeness of data filling.

As for the data features of pipeline GIS, in Figure 2, the rows related to the probability of pipeline failure are the

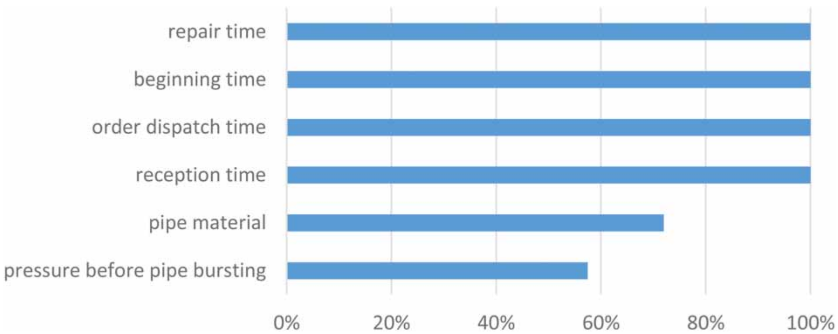

Figure 1 | The proportion of relevant fields in the repair record.

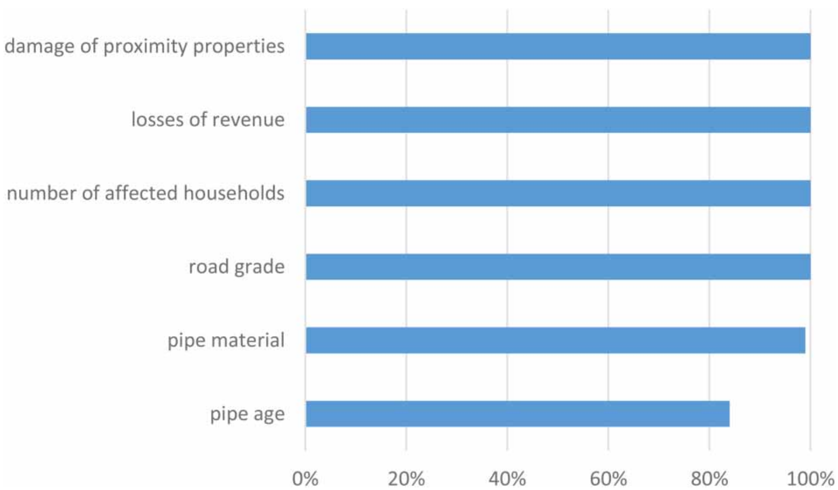

Figure 2 | The proportion of relevant fields in the GIS of pipes.

pipe material, pipe age, and road grade; the rows related to the potential consequences of pipeline failure are the number of affected households, repair time, loss of revenue, and damage of proximity properties. The proportion of filled data are shown in Figure 2. The scores of road grade, number of affected households, loss of revenue, and damage of proximity properties were calculated by using different sources of data combining with pipeline GIS, and the completeness of data is high. The number of affected households was counted from 1/500 user details with high confidence; loss of revenue was estimated from assets system with secondary confidence; damage of proximity properties was counted from the number of proximity households with low confidence at this time, whereas it can be fully evaluated if the data of flooding from pipe bursts is obtained. With regard to the pipeline material, a total of 661 terms of data were revised with the help of TWC in the first stage, and we had improved both the completeness of data and confidence significantly, getting the higher weight.

The water pressure data were obtained through either the SCADA monitoring system or provided by various districts of TWC. Both the completeness and the confidence of SCADA are all high because they are the actual monitoring data. The road traffic data, which was estimated from the traffic statistics of the Ministry of Transportations and Communications, have high completeness but low confidence, giving the lower weight.

RESULTS AND DISCUSSION

In this study, we adjusted the weights on the basis of real quality of obtained data, and used questionnaires to adjust the correlation of sensitivity among all the factors. These objects contained members of this research who are familiar with the quality of all data, personnel who had related foreign experiences before, and the TWC staff who are responsible for leak repairs. Due to the large number of personnel whose work sites are all around Taiwan and abroad, we decided to use the more efficient electronic questionnaire in this study, and it was conducted from April 1, 2005 to April 18, 2005, and is described as follows.

In this questionnaire, we asked the respondents to give a score ranging from 1 to 5 regarding the sensitiveness of eight factors depending on their own experiences. The respondents of TWC included all the 12 district branches, general offices, Department of Water Loss, management, and regional engineering offices. A total of 334 questionnaires were sent out, among which, 107 are valid. The effective recovery rate of the questionnaire is 32%.

Charts of the average and distribution of probability of pipeline failure are shown in Figures 3 and 4, respectively. The results show that the average ranks of both pipe material and water pressure occupy the higher order, and most of them are concentrated between 4 and 5, which means most of the respondents have a consensus on the high order of these two factors. The rank distribution of road traffic is similar to that of the pipe age, and most are concentrated between 3 and 5. Accordingly, we ranked the order of average value as pipe material, water pressure, road traffic, and then pipe age, and the results are also consistent with the weights given before.

Chart of the average and distribution of consequences of pipeline failure are shown in Figures 5 and 6, respectively.

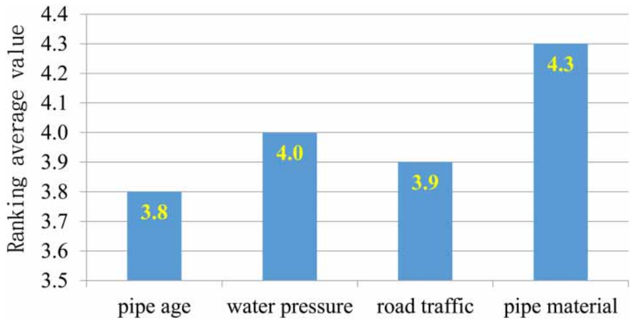

Figure 3 | The sorting average value of probability of pipeline failure.

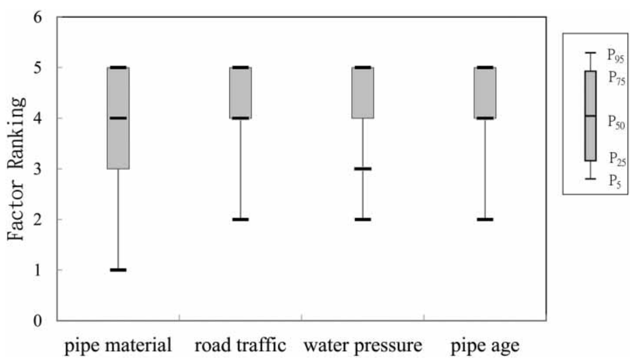

Figure 4 | The sorting distribution of probability of pipeline failure.

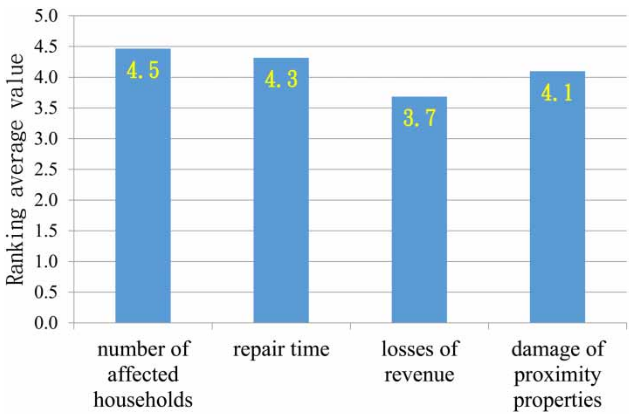

Figure 5 | The sorting average value of effect degree of potential consequence.

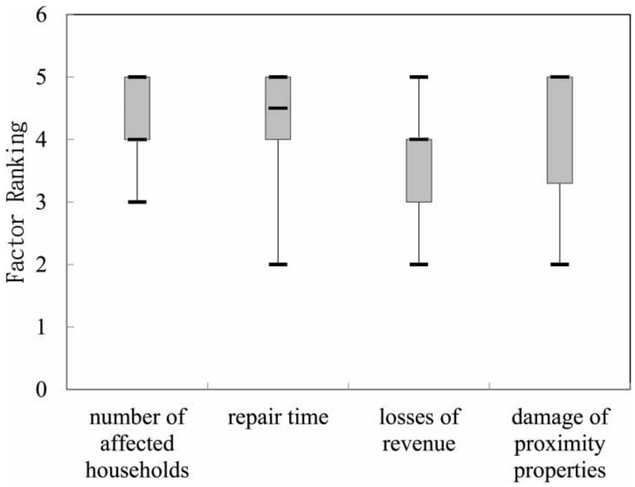

Figure 6 | The ranking distribution of effect degree of potential consequence.

According to the results, the average ranks of both the number of households and repair time are higher, and most are concentrated between 4 and 5, which mean that most of the respondents have a consensus on the high order of these two factors. The average rank of revenue loss is lower than that of damage of proximity properties, and most are concentrated between 3 and 4. Accordingly, we ranked the order of average value as the number of affected households, repair time, damage of proximity properties, and then pipeline revenue loss, and the results are also consistent with the weights given before.

The risk scores of the object pipelines were obtained from the calculation algorithm mentioned in the previous section. However, considering that the pipeline failure is a dot event (e.g., pipeline bursting), if later projects relate to detecting/monitoring/renewing/replacing high-risk pipelines, it is suggested that the projects should be concentrated on either the pipelines buried underneath in the same batch at the same time or a complete road section for the purpose of identification. In terms of the risk ranking, we set a specific section as an evaluation unit (e.g., road length between 500 m and 2 km, mainly indicate by the name of the road). The object pipeline with the highest risk score was selected, representing the entire evaluation unit for ranking. The evaluation units of discrete pipeline, as well as the station facilities, are beyond detection significance, and therefore are not subsequently ranked.

Regarding the evaluation unit of probability of pipeline failure and potential consequence of pipeline failure, scores of each unit were classified into three levels, and thus a 3×3 risk matrix was built. Each unit was assigned to high, secondary high, middle, and low risk level, respectively (Figure 7).

According to the risk matrix, the statistic of pipeline length for each risk evaluation unit is shown in Figure 8, which reveals the length of high risk is 171 km (7.7%), the secondary high risk 574.6 km (25.8%), the middle risk 714.3 km (32%), the low risk 701.5 km (31.5%), and the unranked length is 67.8 km (3.0%). The risk classification map for each region is shown in Figure 9; for example, the first district management office, the high risk is 8,028 m, and the remaining areas are the second highest risk,

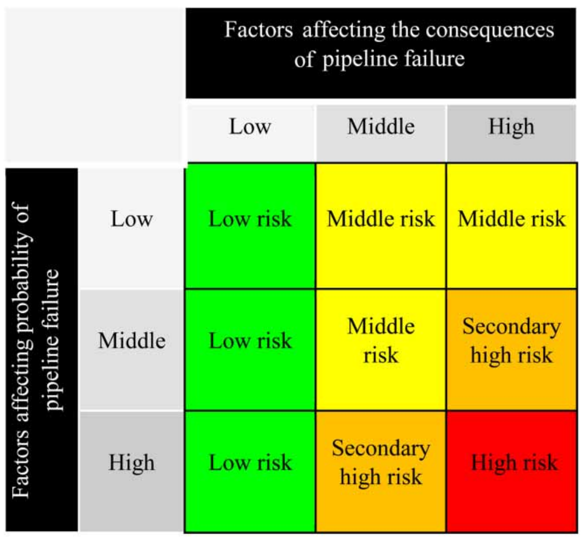

Figure 7 | The risk matrix for the ranking of evaluation units.

Risk level	GIS color classification	Number of evaluation units	Length of pipeline (km)	Percentage of the total length
High risk		114	171.0	7.7%
Secondary high risk		440	574.6	25.8%
Middle risk		577	714.3	32.0%
Low risk		667	701.5	31.5%
No ranking	-	447	67.8	3.0%

Figure 8 | Evaluations of pipe length of various risk levels for TWC.

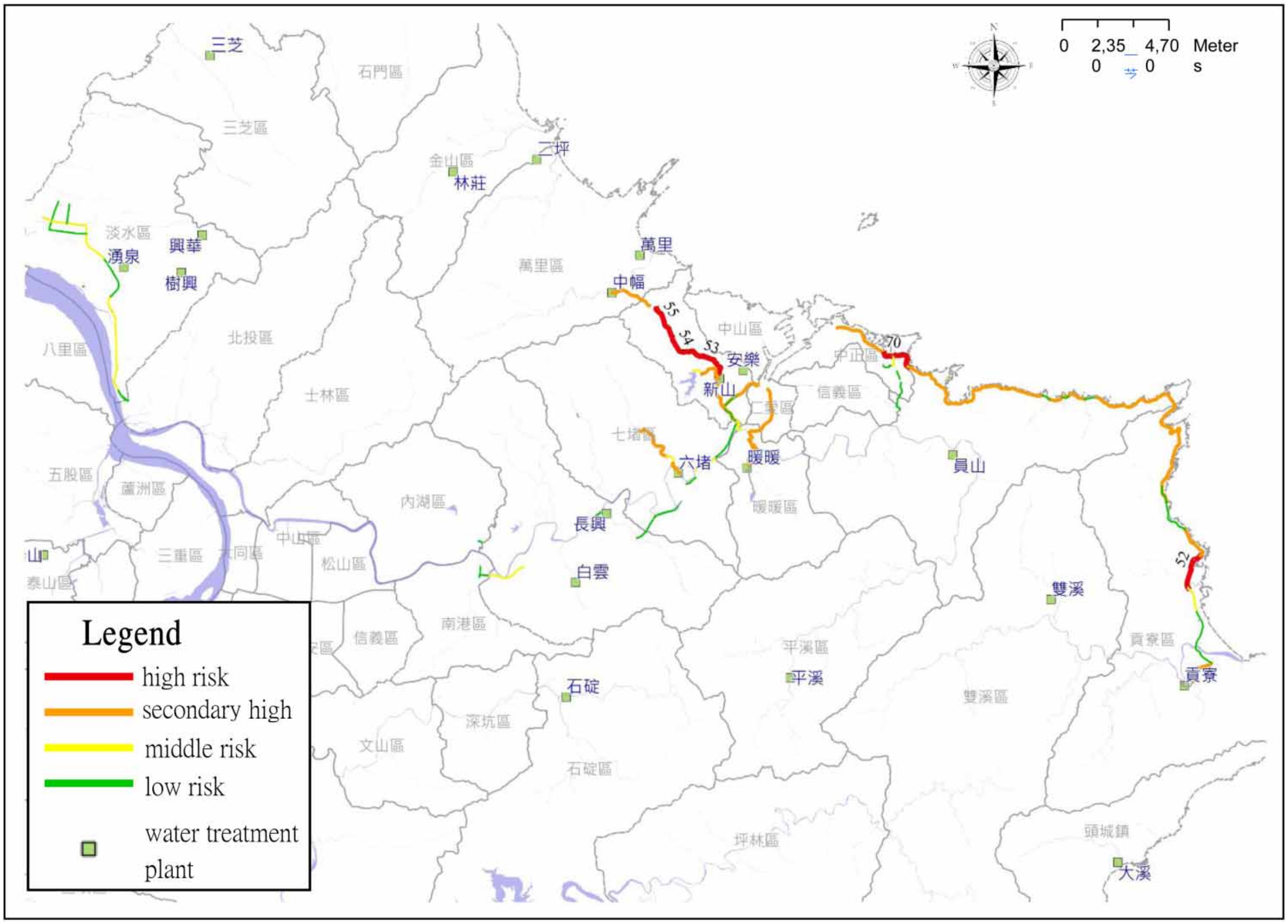

Figure 9 | Examples of risk classification map in a district of Taiwan.

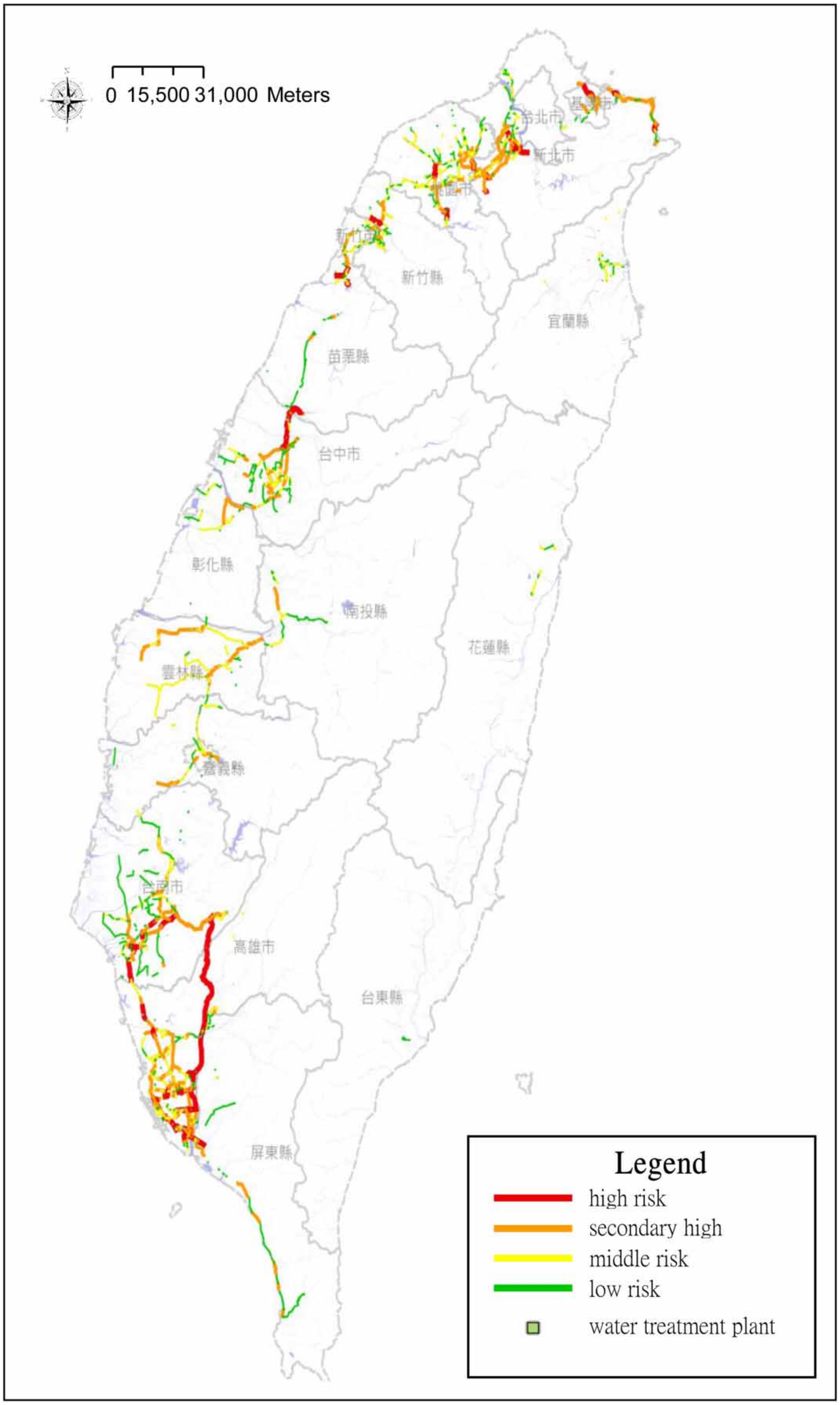

Figure 10 | Risk evaluation unit classification map of Taiwan.

medium risk, and low risk. According to the risk matrix evaluation results, combined with the GIS system, the risk assessment chart of the Taiwan assessment unit is shown in Figure 10. The high-risk area can be used as the pipeline inspection and replacement order.

In this study, we selected some factors, including the pipeline bury year, material, operational water pressure, and heavy vehicle traffic, to predict the probability of pipeline failure. When executing pipeline detection in the future, the results can be fed back to this risk model. By increasing the factors and adjusting the weights for re-evaluation, the accuracy of probability of predicting pipeline failure can be improved effectually.

Events of water supply failure have had a significant impact on the TWC regarding the aspects of financial losses, revenue, and reputation. If a large-diameter pipeline bursts, it may damage the properties of proximity households, and even affect the safety of residents.

CONCLUSION

In this research, eight factors were selected, and each was given a weight for processing the multi-factor pipeline analysis. We assigned the representative risk scores to 2,245 pipeline evaluation units; after excluding the evaluation units belonging to discrete pipelines or station facilities, the remaining 1,798 pipeline evaluation units were used to process risk classification and ranking. The results are presented by the functional module of a pipeline potential map, providing users with intuitive as well as visual risk information.

This study also established the 3×3 risk matrix; each evaluation unit corresponded to one of the four risk levels: high, secondary high, middle, and low, thereby processing classification by the risk matrix. The large-diameter (above 800 mm) pipeline length statistic for various risk evaluation units of TWC reveals the length of high risk is 171 km (7.7%), the secondary high risk 574.6 km (25.8%), the middle risk 714.3 km (32%), the low risk 701.5 km (31.5%), and the unranked length is 67.8 km (3.0%). Finally, this study defined a risk matrix in view of pipeline detection in the future, and classified the risk level of evaluation units.

The detection frequency for each risk level referred to not only the experiences of foreign water companies but also the safety evaluation frequency of high-risk pipe from the 'Technical specification for inspection and safety assessment' of Taiwan Water Resources Department. We schemed the short-, medium-, and long-term detection plan according to the risk levels of the object pipelines, and the detection frequencies were classified as high risk with the check term every five years, sub-high risk with planned check for five to ten years, medium risk with checking/monitoring as needed, and low risk with quick repair and no need to take measurements and monitoring.

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