An improved method of estimation for risk loss cost in natural gas network layout optimization

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ABSTRACT

We develop an improved layout optimization procedure, in which the BP neural network is applied and three different independent variables are analyzed. Herein, the procedures include two crucial steps. The first step is to forecast two risk loss costs by applying a neural network based on three different independent variables, and the second step is to verify the effective of the new estimation by using the predicted risk cost as the edge weight of the minimum spanning tree algorithm. The new method is applied in three different cases, leading to three distinct optimal layout. The results indicate that the economic benefit of using four independent variables is greater than the economic benefits of using three and two independent variables. Then, two optimal strategies for the pipeline network layouts are presented. These strategies realize a 1.54 to 13.23% greater economic benefit than that of the shortest layout.

Keyword: Natural gas network planning
Layout optimization
Neural network
Risk loss
Minimum spanning tree

1. Introduction

In recent years, with the continuous expansion of the pipe network system, various pipeline failures, especially those caused by corrosion, have been discovered. Thus Serious ecological disaster and economic loss were caused and brings great harm to people's living environment. The quantitative calculation method of explosion radius of high pressure natural gas pipeline is studied[1-2]. It is difficult to determine the general method of calculating explosion radius because of the difference in casualties and property estimation caused by different explosion accidents. Pemanand N. Shari J demonstrate that an effective electronic combination of biological and physical parameters can be used to obtain a single environmental sensitivity index for oil spills[3]. Dong Y H proposes a new method, in which the probability of the event is evaluated by applying the expert heuristic of fuzzy set theory[4] A new evaluation method is proposed based on La Maddalena model for Islands of oil slick and coastline, in order to reduce and mitigate the effects of offshore oil dispersal and its detention [5]. Artificial neural network model was proposed to predict pipeline condition average percentage, and its validity is higher than 97% when applied to the validation data set[6]. The modle is expected to help pipeline operators to assess and predict the existing conditions of oil and gas pipeline.

Since 1970, due to the gradual increase of pipeline accidents caused by corrosion, relevant foreign institutions have carried out a series of researches on pipeline corrosion, and many important results have been achieved. Most representative achievements include: ASME B31G standards issued by the national institute of Mechanical engineering (American Society of Mechanical Engineers) in 1991, DNV-RP-F101 and PCORRC method jointly developed by the British standard committee (BSI) and det norske veritas (DNV) in 19990[7-9]. Since the beginning of the 21st century, the finite element theory has been improved, and the research results of pipeline corrosion have been increased, due to the rapid development of computer technology. The results mainly indicate that the critical internal pressure load of pipeline corrosion has higher accuracy, and the overall corrosion outer diameter has too great influence on the ultimate internal pressure load of corroded pipeline. It is mainly based on finite element simulation, supplemented by experiments, and obtained by using nonlinear finite element theory analysis[10-11]. Teixeira AP in [12] an Caleyo in [13] studied the reliability and remaining life of corroded submarine pipelines based on internal pressure. Mourad Nahal et al. studied the failure probability and reliability index of pitting corrosion phenomenon of submarine pipeline Under the action of corrosion and residual stress[14]. Ouk Sub Lee et al. studied the effect of failure probability on corrosion pipeline due to defect depth, pipe diameter, defect length, fluid pressure, corrosion rate, material yield stress and pipe wall thickness[15]. Mohd Hairil Mohd et al. studied the relationship between the internal pressure and bending moment of different corrosion damage and load, and their influence on the residual strength of submarine pipeline, by applying ANSYS nonlinear finite element method[16]. Mohammed S. El-Abbasy et al. presented a reliability prediction model of the pipeline by using artificial neural networks based on historical data in order to keep it running safely[17] In [9] the reasons of natural gas failure are analyzed by using probability statistics, and then Bayesian reliability model is established based on historical fault data. Thus .Finally, the uncertainty and sensitivity of natural gas pipeline are studied. In [18] Integrity of oil and gas pipeline corrosion is evaluated by using the fuzzy logic model. In [19] The markov chain model was established to accurately predict the depth of corrosion pits in oil and gas pipelines. Alma Valor proposed the corrosion data conform to the negative binomial distribution according to the external corrosion shape of buried pipeline[20]. In [21] risk assessment of offshore pipelines is analyzed by applying lateral dynamic stability. In [22] a new layout optimization method is constructed to optimize the risk loss in the layout planning stage. However the theoretical basis of this method is insufficient as the basic data of economic loss are obtained from the actual project.

In this paper, we employ a verification method similar to that described above to develop a better layout optimization procedure in which the theoretical basis for the data that are used to predict the risk loss cost is more sufficient and comprehensive compared to that of the new layout optimization procedure [22]. In the improved layout optimization procedure, a back-propagation (BP) neural network is applied in the first step based on three different independent variables because the economic benefit with four independent variables is greater than the economic benefit with three and two independent variables, and this method realizes a 1.54 to 13.23% greater economic benefit than that of the shortest layout.

2. The critical steps of the new layout optimization

The problem statement of the new layout optimization is to synchronize the minimum value of risk loss and total cost of natural gas pipeline networks at the planning stage. The mathematical model and calculation procedures, which constitute the crucial framework of this problem, are described in the following subsections.

2.1. The predicted risk loss cost

The layout optimization presented by Sanaye ([23]) is committed to minimizing the total cost, which contains investment and operating costs. However, without risk loss, the layout optimization results are not entirely consistent with practical application, which is mainly due to the crossover and mutation of the genetic algorithm (GA) program. GA is based on the random combination of one group of network data, and hence, the as-obtained optimal layout is not suitable for pipe-laying. In our work, a feasible layout decision is obtained by employing graph theory because the original and input data are derived from the actual pipeline laying path.

The edge weight used in this study is expressed using cost functions for the leakage risk and corrosion risk according to graph theory, in which different types of practical data can express the edge weight of the network graph. The corrosion prevention cost, corrosion risk loss cost, leakage risk loss cost and total investment cost are used in the corrosion risk cost.

On the one hand, the leakage risk cost should be the focus of medium- and low-pressure pipeline networks in urban areas because environmental economic losses caused by corrosion and third-party damage are very large. On the other hand, the corrosion risk cost should be the focus of long-distance high pressure pipeline networks in suburban areas because the leakage risk loss cost is too small to be of concern ([24]). The corrosion risk cost includes two aspects: one is the pipeline corrosion risk cost during the construction and operation periods and the other is the economic loss due to corrosion leakage. The two aspects are associated with the pipe network's geographical environment, which is often affected by random disturbances, such as the flow of people, surrounding pipelines and buildings around the pipeline. Therefore, the risk levels of soil corrosion can be used as independent variables to fit the corrosion risk function([25]). Soil components are often treated as an index in buried pipeline corrosion because buried pipelines are exposed to varying types of soil in different regions([26]). Thus, the two costs (i.e., leakage risk cost and corrosion risk cost) can be summarized by the following formulas.

Leakage risk cost = leakage risk loss cost + investment cost (1)

Corrosion risk cost = leakage risk loss cost +investment cost + operation cost (2)

The investment cost and operation cost per unit length of pipeline include material, labor, installation, purchase and transportation costs, which depend on the pipe length, pipe diameter, and electricity used by the compressor stations. The leakage risk cost, that is, the economic loss caused by social environmental consequences and casualties, has been substantial in recent years because accidents have occurred frequently with the increasing number of pipeline transmission networks that have been built. Particularly, these costs are calculated by using the net present value of an actual project. Hence, it is not necessary to estimate the input parameters to fit the two cost functions. Moreover, the more comprehensive these costs are, the more accurate the risk cost function will be. Equation (1) emphasizes the leakage risk loss cost that is included in the above two functions, as it is the main difference between urban and suburban areas.

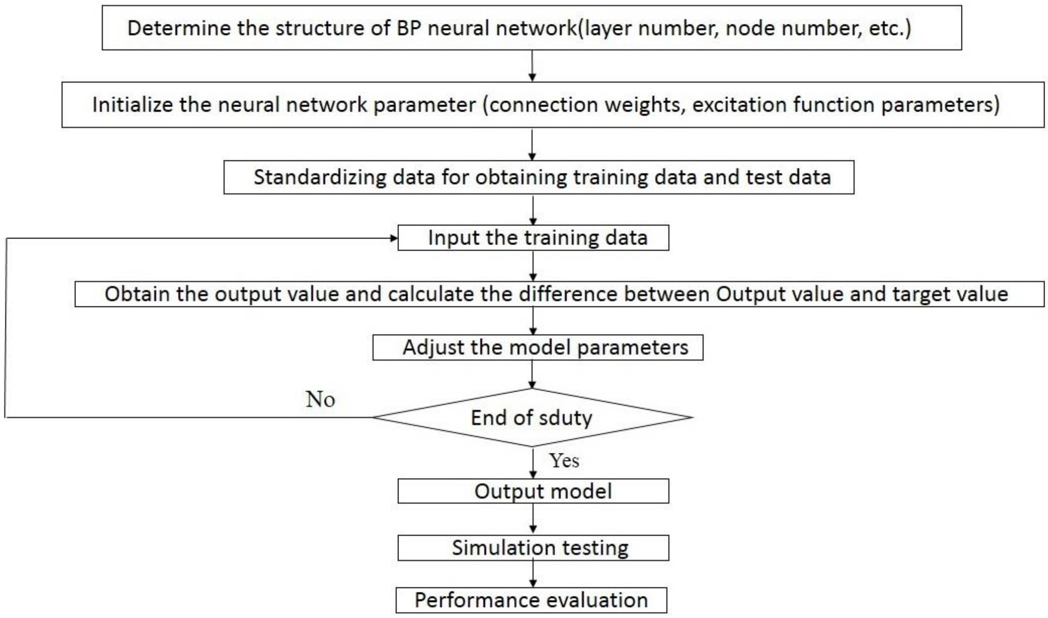

Figure 1. Algorithm flow diagram of the BP neural network

2.1.1 Train BP neural network

Both the corrosion risk cost and leakage risk cost vary with changes in the pipeline soil environment, and four chemical components of soil, i.e., the resistivity x, moisture content y, natural potential（-V）z, and pH value w, are defined as the independent variables of the cost function. Thus, the three different independent variables are defined as two independent variables (x and y), three independent variables (x, y and z), and four independent variables (x, y, z and w). The actual cost, i.e., the training data and testing data are obtained according to the historical data of middle pressure gas network in urban and suburban, which is gathered by SCADA system of Chongqing gas group, and based on formulas (1) and (2). 40 pipe section data are divided into 30 training set data and 10 testing data, and have the similar distribution. The flow diagram of the BP algorithm is shown in Figure 1. The parameters of the trained neural network are as follows: the train epochs equal 1000, the hidden layer has 9 neurons, the output layer has 3 neurons, the hidden layer activation function is tansig, the output layer activation function is purelin and the training function is trainc, based on MATLAB R2010b. The influence of neuron number in hidden layer on model performanc is analyzed in order to choose the number of neuron, because this is the determinant for avoiding over fitting. **Figure 2** describes the effect of neuron number on neural network performanc. The mean of determination coefficient R^2 is obtained based on 10 operating results to reduce the impact of the initialized weight value and valve([27]; [28]).

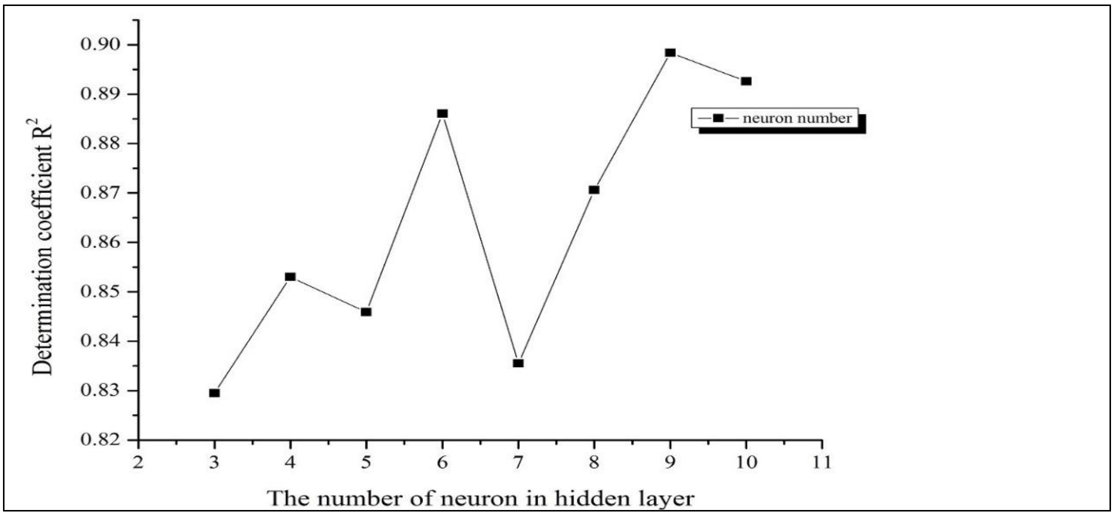

Figure 2. the effect of neuron number on neural network performanc

Thus the mean of determination coefficient R^2 is maximum when the number of hidden layers is 9. 10 operating results of R2 corresponds to the neuron number as listed in **Table 1**.

Table 1. 10 operating results of R2 corresponds to the neuron number

The neuron number in hidden layer	Determination coefficient R2		
	maximum	minimum	mean
3	0.9648	0.6514	0.8295
4	0.9468	0.6807	0.8530
5	0.9295	0.6209	0.8459
6	0.9651	0.7796	0.8861
7	0.9437	0.6426	0.8355
8	0.9435	0.7741	0.8706
9	0.9598	0.8254	0.8984
10	0.9663	0.7373	0.8926

2.1.2 Performance evaluation

The predicted value are verified by comparing the actual investment cost and predicted investment cost of the testing data. The investment cost is equal to the corrosion risk cost minus the leakage risk cost. The investment cost, which is the actual installation cost for the network area and is relatively stable, is defined as the error evaluation criteria of the fitted risk cost. The two investment costs are predicted by the above trained neural network, as shown in Figure 3.

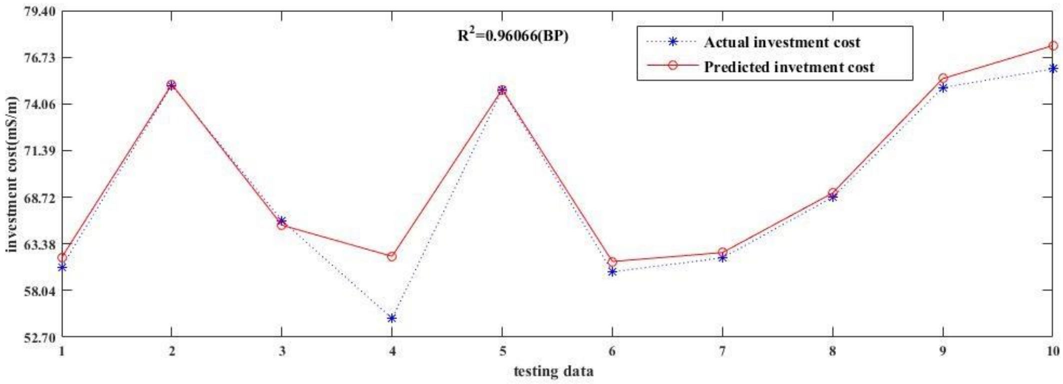

Figure 3. The predicted value of testing data

Similarly, the results shown in **Figure 3** include those based on three independent variables and four independent variables. The change in the error based on two independent variables and three independent variables is not obvious, but the error based on four independent variables is significantly reduced. In addition, the maximum error value of the cost function, which is less than 20%, was calculated by comparing the fitted investment cost and the actual investment cost according to the scatter plot of the data of the two groups, as shown in Figure 1. The two strategies obtained by the new procedures for decision-makers to plan optimal network layouts with maximum benefits and minimum risk were not affected by the 24% error value. The important theoretical basis to verify the predicted risk cost is shown in **Figure 4**.

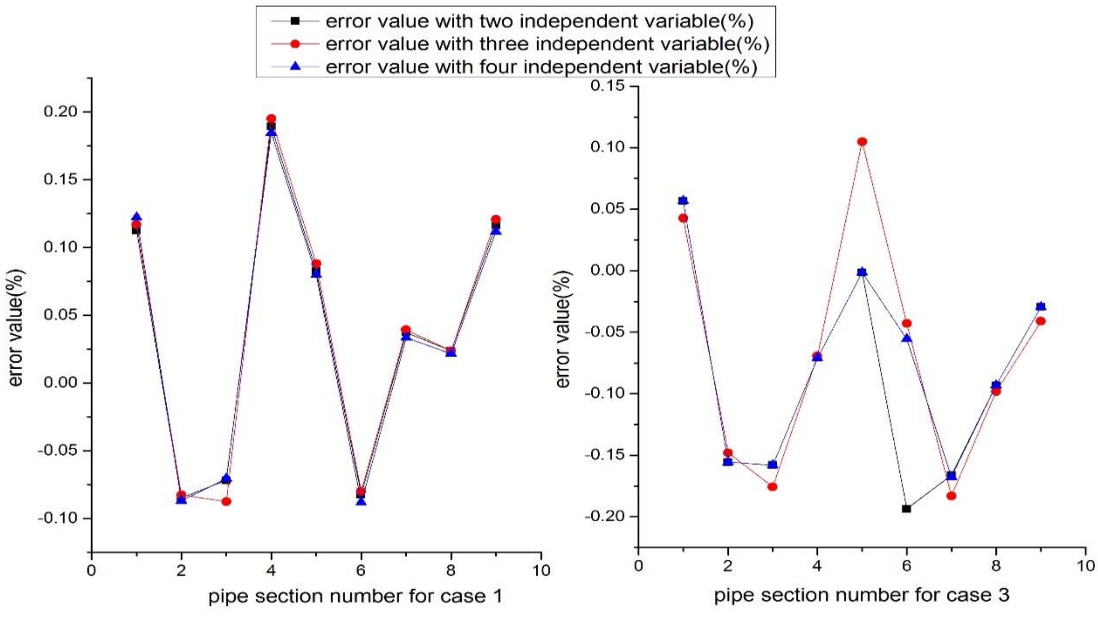

Figure 4. Error variables of the investment cost with three different independent variables

2.2. The new procedures

Based on the two risk costs predicted by the trained neural network, the new procedures are depicted in **Figure 5**.

Step 1 (test point): Set the test point (i.e., the pit number) according to the principle of interval, 500 m or 1000 m, and record the resistivity and moisture content of the soil chemical elements by applying GIS. Notice that this step is based on the planning and building of a pipeline network.

Step 2 (actual cost): Collect the local actual leakage risk loss cost caused by a leakage accident, corrosion loss cost, investment cost and operation cost. These base costs act as the basic data for training the neural network. Notice that this step is based on the building of a pipeline network.

Step 3 (neural network): Train the neural networks according to the actual cost in step 2.

Step 4 (predicted risk cost): Calculate the two risk costs based on three different independent parameters.

Step 5 (minimum spanning tree): Determine the value of the edge weight based on the previous procedures and then employ the minimum spanning tree to gain the optimal layout.

Step 6 (optimal layout): Analyze the optimal results and determine the optimal layout strategy according to the positives and negatives of the benefit value.

Figure 5. Procedure for solving for the optimal layout of a pipe network

2.2.1. Edge weight

The corrosion risk cost and leakage risk cost are used as edge weights. The edge weight value of each pipeline in various soil environments is different due to two main factors. One is that the soil chemistry elements are independent parameters of the two risk cost functions, which vary in diverse environments. The other is that the cost used to train the neural network changes due to altered areas or markets. The leakage risk loss cost in urban areas is larger than that in suburban areas because urban populations are greater. Thus, the edge weight varies with differences in the pipeline area or environment.

The two main factors, which include soil erosion, third parties, and the surrounding construction, relate to the soil chemistry, which includes the soil resistivity, redox potential, soil pH value, soil moisture content, soil salt content, and tube potential. Herein, two elements, resistivity and moisture content, are selected to be the independent parameters of the risk cost function to calculate the values of the edge weight.

2.2.2. Minimum spanning tree algorithm

The Kruskal algorithm is a greedy algorithm, in which the smallest edge weight was selected from the rest of the side and then added to a set of edges in each step. The smallest weight of the edge, which is connected to two trees, one tree, or a new tree, it is added to the forest. Then, when all of the vertices are connected, the minimum spanning tree is finally determined. Thus, the program of "[T, c] = krusf (b, 1)" is used in MATLAB: T is an "n" row by 2-column matrix, in which "n" is the number of pipe segments, and its column numbers are the starting nodes and terminal nodes a.

The variable c expresses the sum of the weights. Finally, b is an "n" row by 3-column matrix, and its column elements are starting nodes, terminal nodes and edge weights.

3. Case study

The pipeline networks of the three cases are: medium pressure in urban areas, medium-high pressure A in suburban areas, and medium-high pressure B in suburban areas (Jin An, 2016). The main differences are as follows.

1 The same area is used for the first case and second case so that the training of the neural network is the same but the three different independent variables are not;

2 A different area is used for the third case so that neither the training of the neural network nor the independent variable is the same.

3 The first case and third case are for urban areas, while the second case depicts suburban areas.

Soil data are shown in **Table 2**, and we suppose that the length of each pipeline in the initial layout is the same for the three cases as shown in **Figure 6**.

Table 2. The chemical indices of soil test points

Pit No.	Soil texture	pH value	Resistivity (Ω·m)	Moisture content (%)	Natural potential (-V)
1	Loam	24.56	21.84	8.3	0.55
2	Loam	48.68	30.46	6.46	0.542
3	Clay	87.63	26.76	5.52	0.55
4	Clay	17.03	23.39	6.58	0.542
5	Clay	241.9	22.94	6.99	0.54
6	Clay	23.63	22	6.99	0.54
7	Sandy loam soil	24.192	19.03	5.95	0.76
8	Sand	27.69	18.79	5.5	0.772
9	Clay	29.25	18.61	6.27	0.748
10	Clay	38.88	15.73	7.24	0.81
11	Clay	110.77	10.32	8.25	0.82
12	Loam	63.37	14.91	7.05	0.785
13	Loam	105.5	12.19	8.26	0.787
14	Sandy loam soil	241.9	12.13	8.3	0.84
15	Clay	88.9	9.61	5.35	0.88
16	Clay	78.8	11.47	8.02	0.87
17	Sandy loam soil	58.6	13.12	4.84	0.825
18	Sandy loam soil	54.26	13.23	8.38	0.861
19	Loam	51.36	18.01	8.15	0.878
20	Clay	40.35	18.33	5.52	0.85
21	Clay	27.81	20.35	5.7	0.829
22	Loam	25.9	21.13	7.65	0.841
23	Loam	25.11	22	6.31	0.88
24	Clay	21.04	22.56	8.33	0.815
25	Clay	105.5	22.94	4.91	0.834
26	Clay	27.81	30.46	5.38	0.69

27	Loam	48.68	33.36	6.3	0.818
28	Loam	10	17.32	4.35	0.82
29	Loam	8.52	15.51	6.89	0.821
30	Sandy loam soil	200	33.14	8.47	0.61
31	Sandy loam soil	21.2	26.54	5.86	0.52
32	Sandy loam soil	58.6	19.57	7.48	0.67

Thus there are no crossing points between any two pipelines and no closed loops among the pipelines in each production loop. The data for both soil chemical elements and pipeline length are also obtained according to the historical data of middle pressure gas network in urban and suburban, which is gathered by SCADA system of Chongqing gas group.

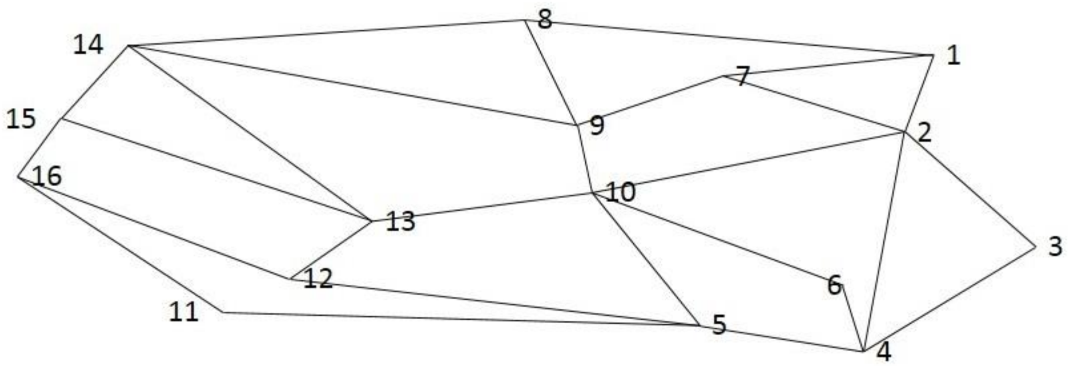

Figure 6. The initial layout for the three cases

3.1. The first case

The two costs of the first example are calculated by applying steps 1 to 5 of the new procedures and the results are as follows by using the minimum spanning tree Kruskal algorithm. Test points (Pit.) are selected between each section of the pipeline, and the soil resistivity, moisture content, natural potential, pH value and soil texture are chosen as the basic soil physical and chemical indices.

(1) The shortest path layout without focusing on the soil erosion risk cost is shown in **Figure 7**.

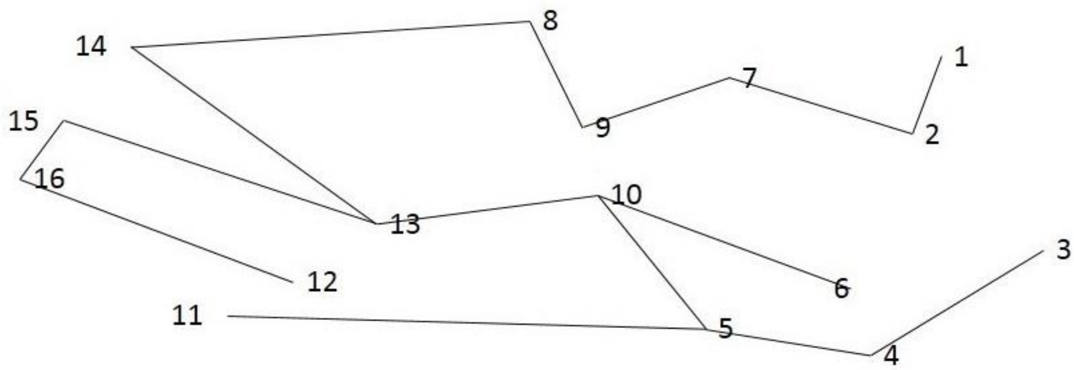

Figure 7. The shortest path layout

The total length of the shortest layout is 8.5450 km, so the leakage risk cost and corrosion risk cost are equal to 0.411729657 m$ and 1.208309333 m$, respectively.

(2)The layout optimization results focused on the leakage risk cost are shown in **Figure 8**.

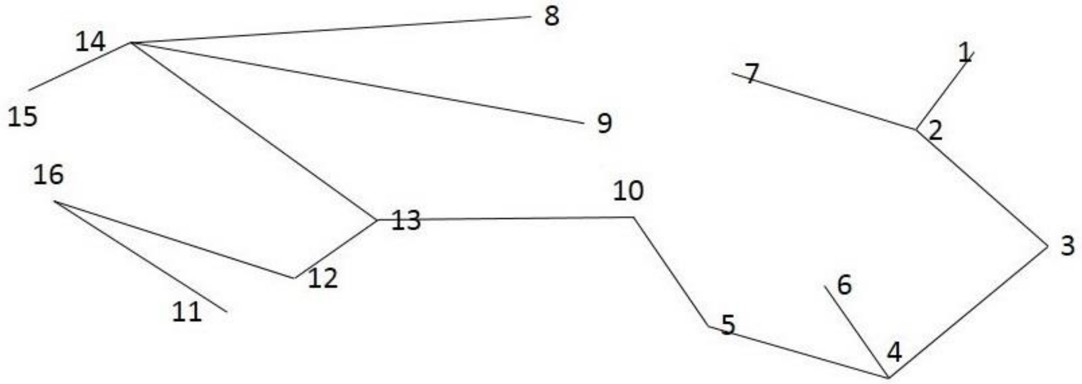

Figure 8. The optimum layout focused on the leakage risk cost

Here, the cost savings are calculated as follows: 0.411729657-0.3887 = 0.023m$.

(3) The layout optimization results focused on the corrosion risk cost are shown in **Figure 9**.

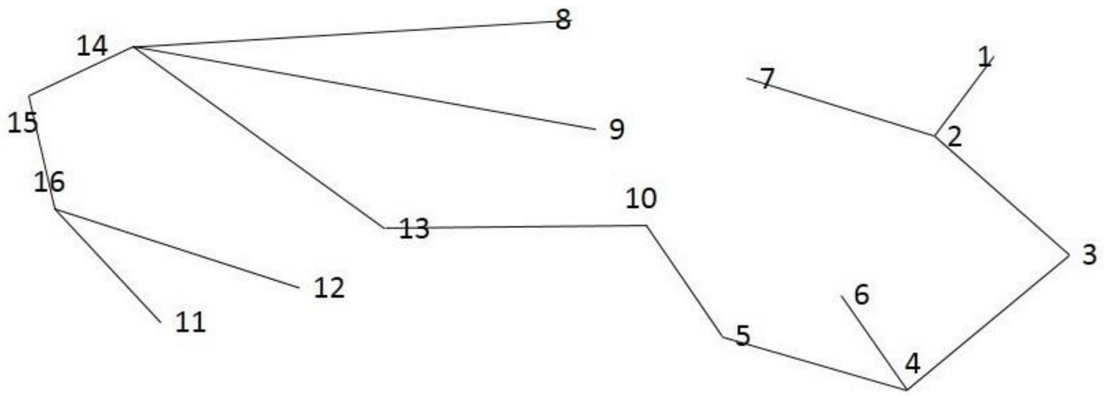

Figure 9. The optimum layout focused on the corrosion risk cost

Here, the cost savings are calculated as follows: 1.208309333-1.176 = 0.0323 m$

3.2. The second case

The two costs of the second example are calculated by the same steps as the first case and The results are as follows by using the same minimum spanning tree Kruskal algorithm.

(1) The length of the pipeline is not changed, so the total length of the shortest layout is also 8.5450 km. However, the area of the network changes as pipelines are planned further away from a crowded city such that the leakage risk cost is smaller. The leakage risk cost and corrosion risk cost are 0.352498212m$ and 1.228044667 m$, respectively.

(2) Layout optimization results focused on the leakage risk cost are shown in **Figure 10**.

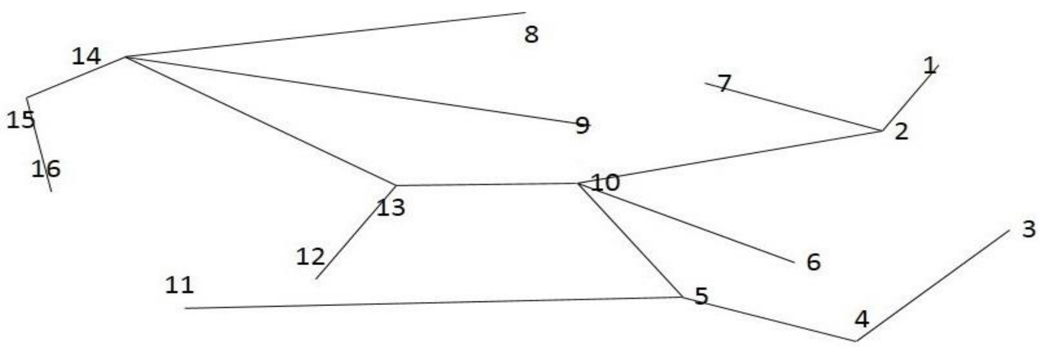

Figure 10. The optimum layout focused on the leakage risk cost for instance 2

Here, the cost savings are calculated as follows: 0.352498212-0.3992 = -0.05 m$.

(3)Layout optimization results focused on the corrosion risk cost are shown in **Figure 11**.

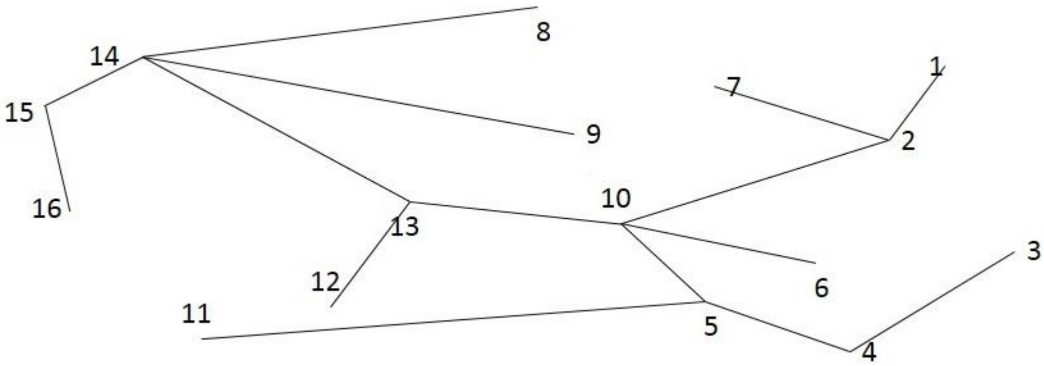

Figure 11. The optimum layout focused on the corrosion risk cost for instance 2

Here, the cost savings are calculated as follows: 1.228044667-1.1966 = 0.03145 m$.

3.3. The third case

The two costs of the third example are calculated using the same steps as in the above two cases and the results are as follows by using the same minimum spanning tree Kruskal algorithm.

(1) The length of the pipeline is not changed, so the total length of the shortest layout is also 8.5450 km. However, the area of the network changes such that the moisture content is different. The leakage risk cost and corrosion risk cost are equal to 0.04247752 m$ and 0.08519975 m$, respectively.

(2) Layout optimization focused on the leakage risk cost are shown in **Figure 12**.

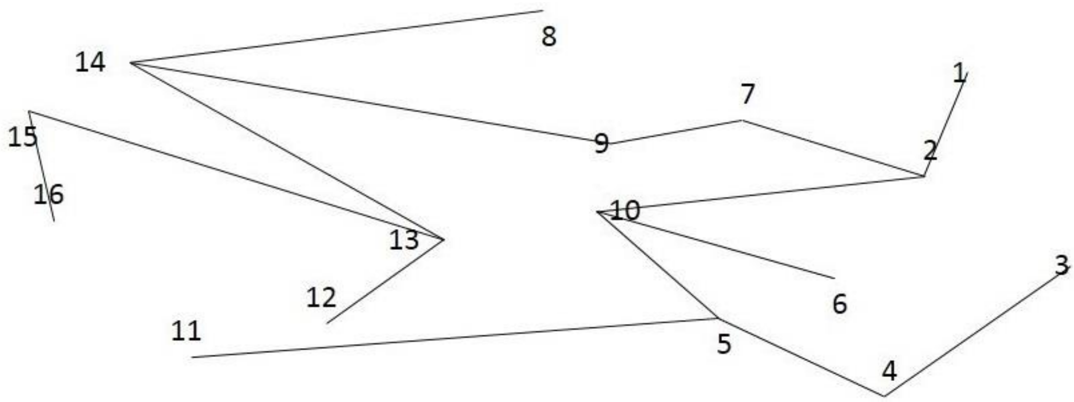

Figure 12. The optimum layout focused on the leakage risk cost for instance 3

Here, the cost savings are calculated as follows: 0.4247752-0.4313 = - 0.0065m$.

(3) Layout optimization results focus on the corrosion risk cost are shown in **Figure 13**.

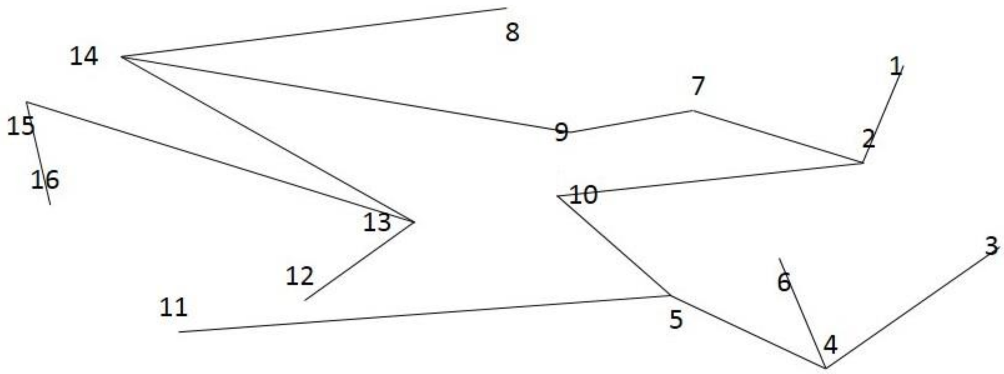

Figure 13. The optimum layout focused on the corrosion risk cost for instance 3

Here, cost savings are calculated as follows: 0.8519975-0.8657 = **-** 0.094318542 m$.

Finally, the two costs and their benefits in three cases with two independent variables are summarized in **Table 3-1**.

Table 3-1. The two costs and their benefits in three cases with two independent variables

Name of cost	Case 1	Case 2	Case 3
The two costs of the shortest layout (m$)	0.411729657 1.208309333	0.352498212 1.228044667	0.4247752 0.8519975
The leakage risk cost and its benefit (m$)	0.3887 0.0230 (5.59%)	0.3992 -0.05(-13.2%)	0.4313 0.0065 (-1.54%)
The corrosion risk cost (m$) and its benefit (m$)	1.176 0.0323 (2.67%)	1.1966 0.03145(2.56%)	0.8657 0.0137(-1.61%)

3.4. Three cases based on two different independent variables

Two different neural networks with three independent variables and four independent variables are applied to the above three cases based on the above procedures. The results are summarized in **Table 3-2** and **Table 3-3**.

Table 3-2. The two costs and their benefits in three cases with three independent variables

Name of cost	Case 1	Case 2	Case 3
The two costs of the shortest layout (m$)	0.411729657 1.208309333	0.352498212 1.228044667	0.4247752 0.8519975
The leakage risk cost and its benefit (m$)	0.3887 0.0230 (5.59%)	0.3992 -0.05 (-13.2%)	0.4313 0.0065 (-1.54%)
The corrosion risk cost (m$) and its benefit (m$)	1.176 0.0323 (2.67%)	1.1966 0.03145 (2.56%)	0.8657 0.0137 (-1.61%)

Table 3-3. The two costs and their benefits in three cases with four independent variables

Name of cost	Case 1	Case 2	Case 3
The two costs of the shortest layout (m$)	0.4114749 1.208552	0.2450157 0.768452	0.4386318 0.8516095
The leakage risk cost and its benefit (m$)	0.3902 0.0213 (5.17%)	0.2126 0.03 (13.23%)	0.4097 0.0289 (6.60%)
The corrosion risk cost (m$) and its benefit (m$)	1.1783 0.0303 (2.50%)	0.7197 0.0488 (6.34%)	0.8666 -0.0150 (-1.76)

4. Results and discussion

Three results are observed according to the values of matrix T and positive a: One result is that the shortest layout of natural gas pipelines is not the optimal layout for minimizing leakage risk loss based on matrix T. The second result is that the integrated error of two predicted rick loss costs decrease (as shown in **Figure 3**) and the economic benefit noticeably increases (as shown in **Figure 14**) with the increase of independent variables. And the last result is that the choice between two costs is an essential determinant of the optimal layout based on **Table 3-1, 3-2** and **3-3**.

As shown from **Figure 7** to **Figure 11**, the layout graph of the three cases observe that these optimum layout are different. Especially in instance 3, as shown in **Figure 12** and **Figure 13**, the total cost is different although the two optimum layout are same. **Table 3-1**, based on two independent variables, the leakage risk cost of the optimal layout offers 5.59% higher economic benefits than that of the shortest layout based on 0.0230, and the corrosion risk cost of the former offers 2.67% higher economic benefits than that of the shortest layout based on 0.0323 from the first case's results. The reality that the economic loss of environmental pollution and casualties caused by leakage is very large in urban areas is entirely consistent with this conclusion. This conclusion, for which the leakage risk cost is suitable for the pipe network layout design of urban areas, is summarized as the first strategy. In the second case, the corrosion risk cost of the optimal layout offers a 2.56% higher economic benefit than that of the shortest layout based on 0.31445. However, the leakage risk cost of the former is higher than that of the latter, which is based on -0.001144861, because the economic losses from environmental pollution and casualties caused by leakage are not large in suburban areas. This conclusion, that corrosion risk loss is suitable for suburban areas, is summarized as the second strategy. In the third case, the **t**wo risk costs of the optimal layout give 1.54% and 1.61% higher economic benefits than that of the shortest layout, based on 0.0065 and 0.0137, respectively, so this conclusion is the same as the first case. This is the best result because the two risk costs are suitable for suburban areas. The two strategies, are obvious based on 5.59% or 2.67% for urban areas, 2.56% for suburban areas, 1.54% or 1.61% for urban areas, as shown in **Table 3-2**, and 5.17% or 2.5% for urban areas, 13.23% or 6.34% for suburban areas, 6.5% for urban areas, as shown in **Table 3-3**. That is the leakage risk cost is suitable for the pipe network layout design of urban areas and corrosion risk loss is suitable for suburban areas. In summary, this optimization layout, obtained by applying the two strategies described above, achieved 1.54-13.23% higher economic benefits over that of the shortest layout; moreover, the economic benefit from four independent variables is greater than the economic benefit from three and two independent variables, as shown in **Figure 14**.

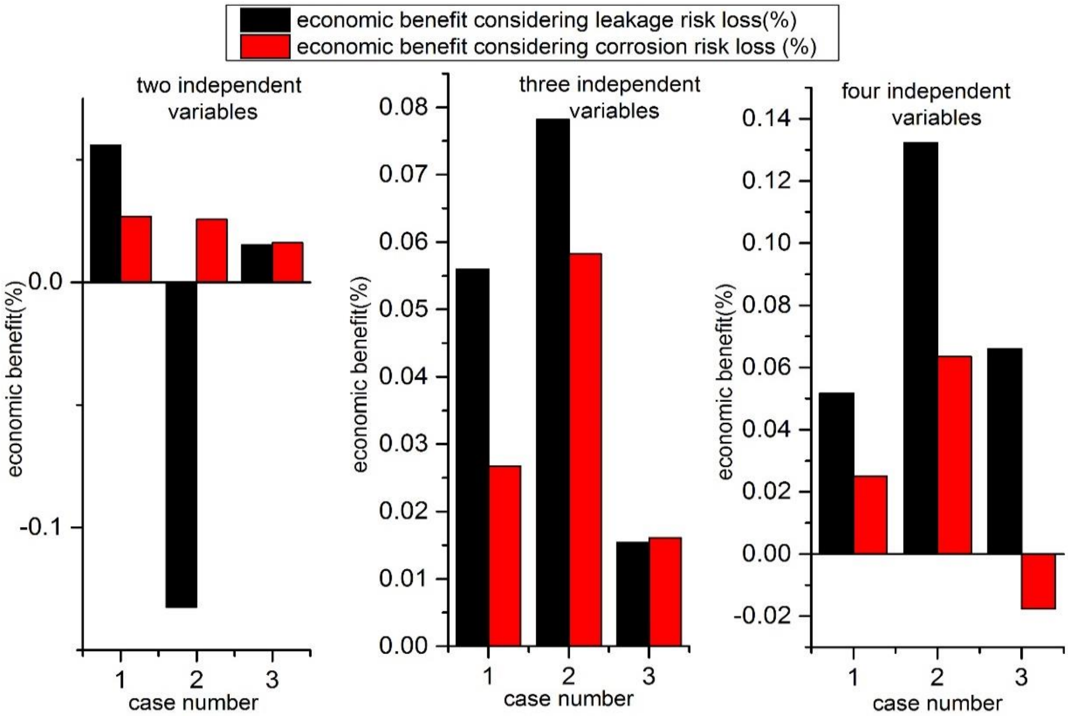

Figure 14. Economic benefit of three cases with three different independent variables

5. Conclusions

This study is distinguished by the problem of new layout optimization, in which new efficient optimization procedures are proposed to obtain a more beneficial layout compared with the shortest layout. In particular, synchronization of the minimum risk loss and total cost of natural gas pipeline networks at the planning stage is achieved. The main thrust of this study is that the two risk loss costs are predicted by applying the neural network based on three different independent variables and are then used as the edge weight to obtain a more accurate risk cost and better economic benefits of the optimal layout. As expected, choosing between the corrosion risk cost and leakage risk cost as the deciding factor is crucial to ensure the best economic and social environmental benefits, and the economic benefits from four independent variables are greater than those from three and two independent variables. Finally, the leakage risk cost could be suitable for low-pressure pipelines in urban areas, as shown in case 1 and in case 3. By contrast, the corrosion risk cost could be suitable for higher-pressure pipelines in suburban areas, as shown in case 2; both could be suitable for suburban areas, as shown in case 1. In summary, the leakage risk cost is used as the deciding factor for urban areas and the corrosion risk cost is suitable for suburban areas, especially because both the corrosion risk cost and leakage risk cost can be used as the deciding factors for the latter when the two benefit values are positive.

6. Outlook

The two costs are accurately predicted by applying a neural network based on three different variables, and the conclusion is drawn that the economic benefit from four independent variables is greater than the economic benefit from three and two independent variables. However, it is notable that the influence of the pipeline environment includes not only the four factors but also the third party destruction and climate conditions. Therefore, the selection principle of the independent variables could be more standardized to make the value of these optimization results more widespread.

The two risk cost functions presented in the first paper can be fit more successfully by considering a greater number of independent variables to obtain better economic benefits from the optimal layout, which is the next step of our research. Thus, leakage risk cost functions containing more parameters (i.e., diameter and pressure) will be provided. A new model and improved algorithm, which is able to synthesize the optimization pipe diameter, layout and city gate station at the beginning of the planning stage, will be developed to achieve overall optimization of pipe networks. These strategies will be important and effective support tools for aiding decision makers in optimizing natural gas transmission networks.

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