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Integrity Assessment of Buried Pipelines under Surcharge Loading Based on a GA-BP Neural Network

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Abstract:

To enable rapid integrity assessment of buried natural gas pipelines subjected to construction surcharge loading, a three-dimensional ABAQUS finite element model incorporating nonlinear pipe–soil contact was developed. The model was validated through mesh-independence analysis and comparison with experimental data reported in the literature, yielding a mean error of 6.32%. The results showed pronounced stress variations in the pipeline within the surcharge-loaded region, with the maximum von Mises stress occurring at the pipe bottom. Based on 100 simulation samples generated using Latin hypercube sampling, a GA-BP neural network model was developed to predict the maximum pipeline stress, achieving a R^2 of 0.9691. An integrity assessment framework was subsequently established by integrating the prediction model with pipeline failure criteria, and stress contour maps were generated to characterize the coupled effects of multiple influencing factors. Engineering application to three in-service pipelines in the Penglai Dengying Block showed that Pipeline No. 3 reached a peak stress of 219.11 MPa, exceeding the allowable stress of 216 MPa and indicating a potential risk of failure. Therefore, surcharge loading should be restricted and appropriate reinforcement measures should be implemented.

Keywords: Buried pipeline; Surcharge loading; Finite element model; Pipe–Soil Interaction; GA-BP neural network

1 Introduction

With the acceleration of global urbanization and the continuous growth in energy demand, natural gas has been increasingly adopted as a clean and efficient energy source, resulting in a rapid expansion of gas transmission pipeline networks. Consequently, temporary soil stockpiles generated by excavation and the operation of

heavy machinery in the vicinity of buried pipelines have become increasingly common [1–3]. In recent years, pipeline leakage and failure accidents associated with surcharge loading have occurred frequently. For example, in 2015, improper soil accumulation around the Chengdu–Chongqing pipeline transportation section resulted in damage at 27 locations along the pipeline [4]. Statistical analysis of 1,249 incidents by the European Gas Pipeline Incident Data Group (EGIG) showed that approximately 48% of pipeline incidents were caused by external interference, with soil stockpiles and heavy machinery representing common threats [5].

To investigate the mechanical response of buried pipelines subjected to surcharge loading, extensive studies have been conducted using theoretical analysis, field testing, and finite element simulation.

Theoretical investigations have evolved from simplified analytical models toward more complex coupled systems. Early studies simplified pipelines as elastic beams resting on elastic foundations, and pipeline responses were commonly evaluated using the Winkler foundation model or Timoshenko beam theory [6]. Marston proposed a theory for evaluating vertical earth pressure on buried pipelines, emphasizing the influence of vertical soil stress on the pipeline [7]. Subsequently, Newmark investigated pipe–soil interaction based on the assumption that the pipeline and surrounding soil deform together [8]. At present, models incorporating both normal and tangential pipe–soil interaction mechanisms have been widely adopted [9]. With respect to load transfer through soil, the conventional Boussinesq elastic half-space solution has gradually become less suitable because it cannot capture soil plastic deformation [10]. The Mohr–Coulomb model and Drucker–Prager hardening model have therefore been widely used to represent the elastoplastic behavior of soil [11]. Nevertheless, these methods generally require assumptions and simplifications regarding loading conditions and pipe–soil contact, which may limit their ability to accurately reproduce the actual mechanical response of buried pipelines.

Considerable research has also been conducted through experimental testing and finite element simulation. Field tests can provide reliable engineering data, but their application is limited by high costs and the difficulty of reproducing complex loading scenarios. Finite element analysis (FEA), owing to its capability to model coupled multiphysics problems, has therefore become a powerful tool for investigating the mechanical response of buried pipelines. Robert et al. employed a three-dimensional finite element model to analyze the maximum stress in buried pipelines subjected to different internal and external loads [12]. Alzabeebee et al. investigated the responses

of buried pipelines to traffic loading under different pipe diameters, burial depths, and pipe material types [13]. Tian et al. [14] validated the accuracy of an FEA model incorporating an improved hardening constitutive model using centrifuge tests.

Machine-learning approaches have also been increasingly applied to engineering problems. Li et al. developed a GA-BP neural network model to predict the failure pressure of water pipelines [15]. Zhang et al. [16] constructed a particle swarm optimization–support vector regression (PSO-SVR) model based on numerical simulation results, providing a rapid method for predicting the axial stress of pipelines subjected to traffic loads. He et al. [17] developed a GA-BP model using numerical simulation data to enable rapid pipeline integrity assessment. However, studies applying machine-learning methods to pipeline integrity prediction under surcharge loading remain relatively limited.

A research gap therefore remains in the rapid integrity assessment of buried pipelines subjected to surcharge loading. In this study, a three-dimensional finite element model incorporating nonlinear pipe–soil contact is established in ABAQUS to characterize the distribution of the maximum von Mises stress in buried pipelines under different surcharge-loading conditions. Subsequently, a GA-BP neural network prediction model is developed through coupled ABAQUS–MATLAB simulations. By further integrating the prediction model with pipeline strength design criteria, an integrity assessment procedure is established to enable rapid identification of construction-related surcharge risks.

The main innovations and contributions of this study are summarized as follows:

1. A nonlinear coupled pipe–soil finite element model is established to investigate the distribution characteristics of von Mises stress in buried pipelines subjected to surcharge loading and to identify the critical pipeline location associated with failure.

2. A GA-BP neural network model is trained using 100 sets of simulation data to achieve rapid and accurate prediction of the maximum pipeline stress.

3. An integrity assessment framework for buried pipelines under surcharge loading is established in accordance with GB 50251-2015, Code for Design of Gas Transmission Pipeline Engineering [25], and is successfully applied to three buried pipelines in the Penglai Dengying Block of PetroChina Southwest Oil & Gas Field Company.

2. Numerical Model of Buried Pipeline under Surcharge Loading

2.1 Geometric Model

Based on ABAQUS, a numerical model was developed to investigate the mechanical response of a natural gas pipeline subjected to construction surcharge loading. The model was simplified according to actual field conditions in PetroChina Southwest Oil & Gas Field Company and consisted of a buried pipeline and the surrounding soil. The surcharge area considered in this study was 5 m × 10 m. To minimize boundary effects, the soil domain was established with dimensions of 50 m in length, 50 m in width, and 5 m in depth, as shown in Fig. 1.

The pipeline was made of L360 pipeline steel, with a Young's modulus of 206 GPa, a Poisson's ratio of 0.3, a density of 7850 kg/m³, and a yield strength of 360 MPa. To accurately characterize the nonlinear behavior of the pipe material in the plastic regime, the constitutive relationship of the pipeline was described using the Ramberg–Osgood model. The model predictions showed good agreement with the experimental results, as illustrated in Fig. 2. The soil was modeled using the Drucker–Prager (D–P) elastoplastic yield criterion. Compared with the relatively simple Mohr–Coulomb model, the D–P model provides better numerical convergence. The corresponding physical properties and hardening parameters are listed in Tables 1 and 2, respectively [18].

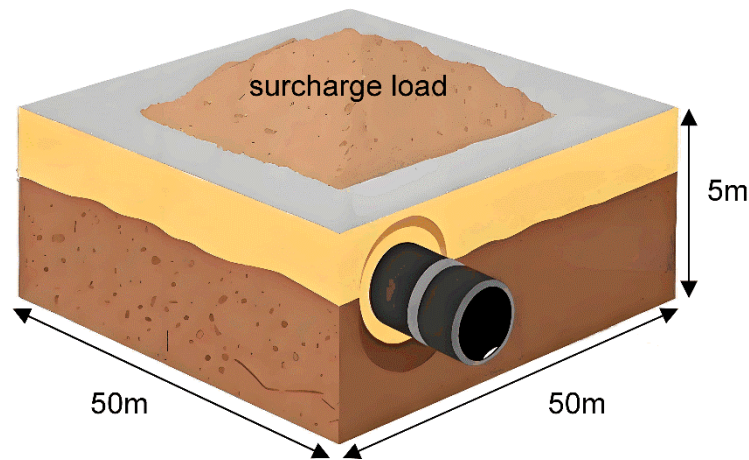


Fig. 1. Schematic diagram of the pipe–soil geometric model

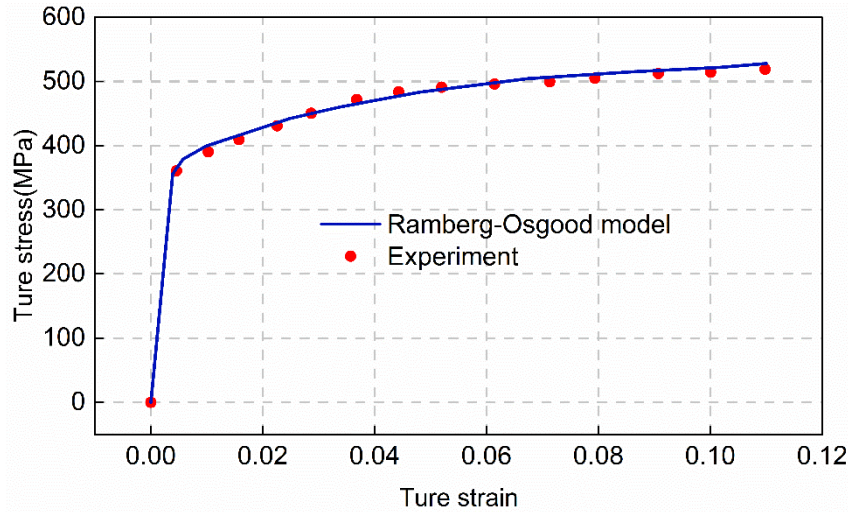


Fig. 2. True stress–strain relationship of L360 steel

Table 1. Basic parameters of the soil model

Density (kg/m ³)	Young's Modulus (MPa)	Poisson's Ratio	Angle of Friction (°)	Flow Stress Ratio	Expansion Angle (°)
1780	14.4	0.4	36	1	0

Table 2. Hardening parameters of the Drucker–Prager model

Yield stress/ MPa	0.17	0.65	0.75	0.8	0.85
Absolute plastic strain	0	0.035	0.051	0.073	0.092

2.2 Pipe–Soil Interaction

To accurately characterize the nonlinear contact behavior between the buried pipeline and the surrounding soil, surface-to-surface contact in ABAQUS was employed to simulate pipe–soil interaction. Because the stiffness of the pipeline is substantially greater than that of the soil, the outer surface of the pipeline was defined as the master surface, whereas the inner surface of the soil cavity was defined as the slave surface. The nonlinear pipe–soil interaction was then represented by specifying appropriate contact properties between the master and slave surfaces.

In the normal direction, a hard-contact formulation was adopted to simulate direct normal contact pressure between the pipeline and soil. In the tangential direction, a penalty formulation was employed to represent frictional behavior, with the coefficient of friction set to 0.3 [19]. The loads applied to the model included the internal pressure of the pipeline, the self-weight of the pipeline and soil, and the soil pressure induced by the surface surcharge.

2.3 Boundary Conditions and Mesh Generation

In the finite element model, the bottom surface of the soil domain was fully constrained, while the normal displacements of the four lateral surfaces were restricted to represent the field boundary conditions. Based on the geometric characteristics of the surface surcharge, the contact area of the surcharge was simplified as a rectangular region measuring 5 m × 10 m, corresponding to a total area of 50 m². The applied pressure was assumed to be uniformly distributed, as shown in Fig. 3.

Eight-node linear brick elements with reduced integration (C3D8R) were used to discretize both the soil and the pipeline. To improve the accuracy of the calculated pipeline response, local mesh refinement was applied in the pipe–soil contact region. The resulting finite element mesh is shown in Fig. 4.

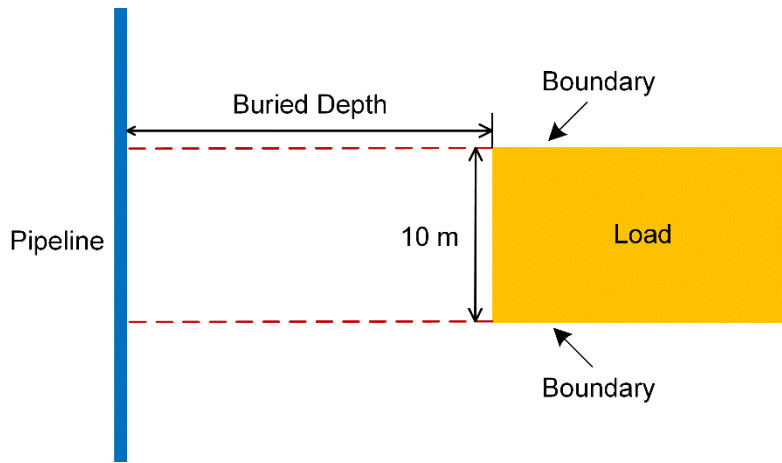


Fig. 3. Spatial distribution of the surcharge load

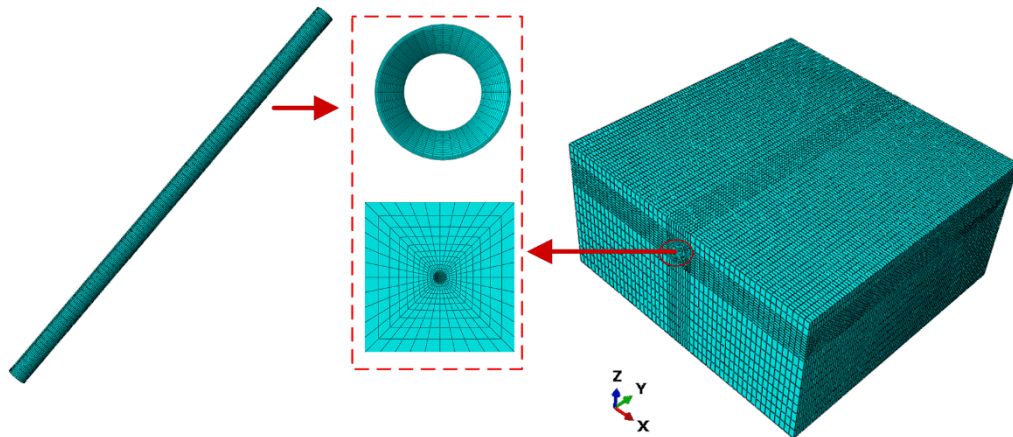


Fig. 4. Meshed pipe–soil model

2.4 Model Validation

2.4.1 Mesh-Independence Verification

Mesh independence was evaluated using the maximum von Mises stress of the pipeline as the assessment parameter. The maximum von Mises stresses obtained using meshes containing between 223,200 and 1,377,416 elements were compared. The results showed a clear monotonic convergence trend as the mesh density increased. When the number of elements increased from 223,200 to 625,440, the calculated stress exhibited relatively pronounced variations. However, once the mesh size exceeded 824,600 elements, the stress response tended to stabilize, with a relative error of less than 1%, as shown in Fig. 5.

To achieve an appropriate balance between computational efficiency and numerical accuracy, a mesh containing 824,600 elements was selected. The same mesh configuration was therefore adopted in all subsequent numerical analyses.

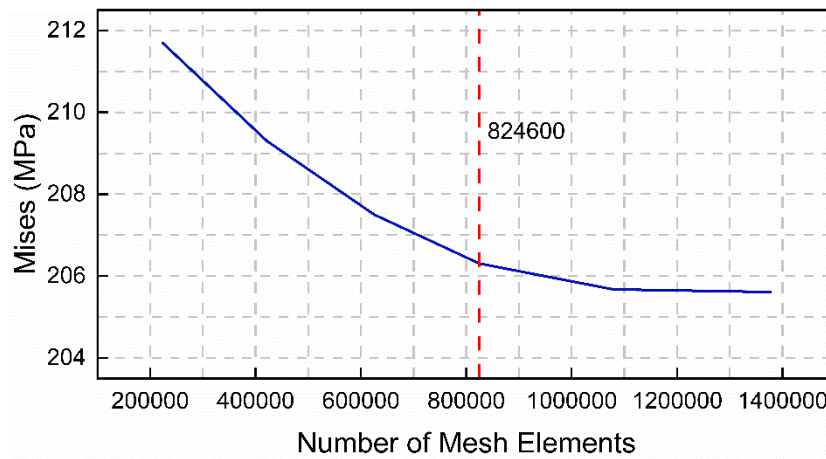


Fig. 5. Mesh-independence verification

2.4.2 Validation of Model Results

A validation model was established with a surcharge pressure of 0.5 MPa, a burial depth of 3 m, and a pipe diameter of DN1200. The numerical results were compared with the experimental results reported in the study entitled “Finite Element Analysis of the Effect of Uniformly Distributed Loads on Buried Pipelines”, as shown in Fig. 6.

The simulation results were in good agreement with the experimental data, with a mean error of 6.32% for the predicted von Mises stress [20]. This agreement indicates that the developed finite element model can reasonably reproduce the mechanical response of buried natural gas pipelines subjected to surcharge loading. The same mesh discretization scheme was adopted for all numerical simulations conducted in this study.

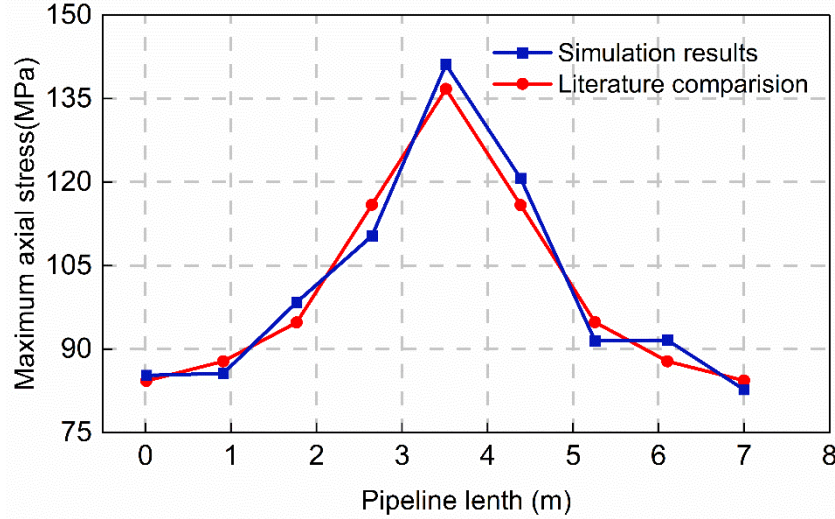


Fig. 6. Comparison between the numerical simulation and experimental results

2.5 Mechanical Response Analysis

To investigate the mechanical response of a pipeline subjected to surcharge loading under representative operating conditions, a baseline case was defined with a pipe diameter of 88.9 mm, a wall thickness of 5 mm, a burial depth of 1 m, and an internal pressure of 8 MPa. A surcharge pressure of 0.4 MPa was applied in ABAQUS, and the resulting distribution of the pipeline von Mises stress was obtained, as shown in Fig. 7. The results revealed distinct spatial characteristics in the pipeline stress response.

(1) Variation in stress along the pipeline

Pronounced stress fluctuations occurred within the main surcharge-affected region of the pipeline (17.5–32.5 m), where the stress response resulted from the combined effects of surcharge loading and internal pressure. At both ends of the pipeline, the influence of the surcharge was negligible, and the stress was dominated by the hoop stress induced by internal pressure, remaining approximately constant at 55 MPa.

The stress distributions also differed markedly among circumferential positions of the pipeline. At the pipe bottom and pipe crown, the longitudinal stress distributions exhibited pronounced symmetric double-peak patterns. At the pipe bottom, peak stresses occurred near the inner sides of the surcharge boundaries, at approximately 21 and 29 m, whereas the stress decreased substantially at the center of the surcharge region (25 m). At the pipe crown, peak stresses occurred beneath the edges of the surcharge area, at approximately 20 and 30 m. In contrast, the stress distribution at the pipe side exhibited a symmetric single-peak pattern, reaching its maximum at the

center of the surcharge region (25 m) and gradually decreasing toward both sides.

(2) Variation in stress around the pipeline cross-section

The maximum von Mises stress around the pipeline cross-section consistently occurred at the pipe bottom. Within the transition regions near the surcharge boundaries (17.5–22.5 m and 27.5–32.5 m), the stress at the pipe crown was greater than that at the pipe side. In the main surcharge region (22.5–27.5 m), however, the circumferential stress distribution showed higher stress at the pipe side than at the pipe crown.

Analysis of the longitudinal and circumferential stress distributions showed that pronounced stress fluctuations occurred within the primary surcharge-affected region (17.5–32.5 m), forming a high-stress zone. The maximum peak stress occurred at the pipe bottom. Therefore, in practical engineering applications, protective measures should be prioritized for the pipe-bottom region directly affected by surcharge loading.

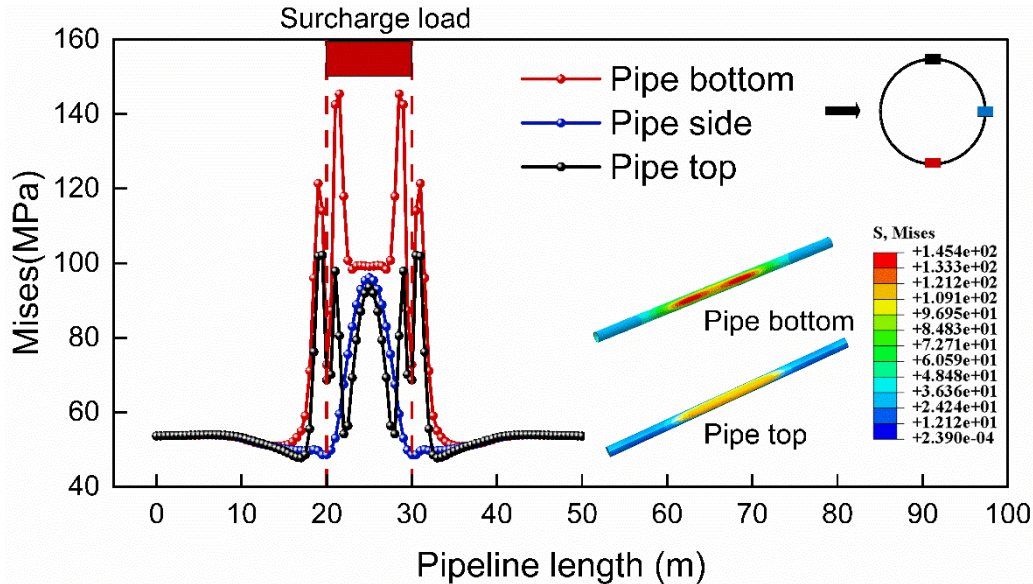


Fig. 7. von Mises stress distributions at different circumferential positions of the pipeline

3. Prediction Model for Maximum Stress under Surcharge Loading

Although numerical simulations can provide high-accuracy results, they are computationally intensive and require considerable expertise from operators, making them difficult to apply directly to rapid integrity assessments of pipelines at construction-crossing sites. In this study, several machine-learning algorithms, including GA-BP, SVM, PSO-BP, and MDT, were investigated [21–24]. A coupled MATLAB–ABAQUS simulation framework was ultimately adopted, and 100 sets of numerical simulation results were generated. Based on these data, a genetic algorithm–backpropagation (GA-BP) neural network was developed in MATLAB to

predict the maximum pipeline stress under surcharge loading. The resulting prediction model was further incorporated into a pipeline integrity assessment framework and applied to three in-service pipelines exposed to construction-related surcharge loading. The results indicated that Pipeline No. 3 was at risk of failure under the investigated surcharge conditions.

3.1 GA-BP Neural Network Model

The backpropagation (BP) neural network is based on the gradient-descent principle and updates model parameters through error backpropagation to achieve accurate predictions. However, its predictive performance is highly dependent on the initial weights. Poor random initialization may require a large number of iterations and may even prevent the algorithm from converging.

To address this limitation, a genetic algorithm (GA) was introduced to optimize the initial parameters of the BP neural network. Through crossover, mutation, and selection operations within a population, the GA performs a broad stochastic search over the solution space and identifies an approximate region containing the global optimum. The optimized initial solution is subsequently passed to the BP algorithm for refined gradient-based optimization. This hybrid strategy substantially reduces the likelihood of the neural network becoming trapped in a local optimum. The flowchart of the GA-BP neural network is illustrated in Fig. 8.

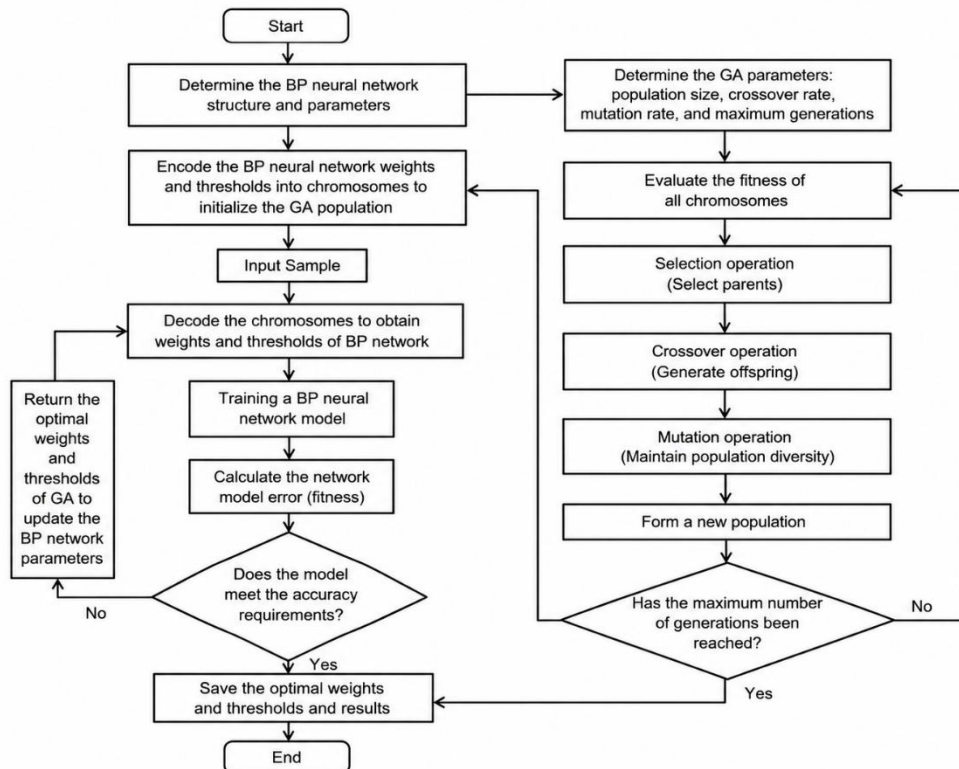


Fig. 8. Flowchart of the GA-BP neural network

The developed neural network contains five input variables—pipeline diameter, surcharge position, internal pressure, burial depth, and surcharge pressure—and one output variable, namely the maximum von Mises stress. Given this relatively simple network architecture, a single hidden layer was considered sufficient. The number of neurons in the hidden layer was determined according to Eq. (1) [18]:

$$k = \sqrt{m + n} + a \quad (1)$$

Where (k) denotes the number of hidden-layer neurons; (m) and (n) denote the dimensions of the input and output layers, respectively; and (a), ranging from 0 to 10, is an empirical parameter used to adjust the network complexity. Neural networks with different numbers of hidden-layer neurons were evaluated in MATLAB.

The results showed that the network with seven hidden neurons provided the best predictive performance. The resulting network architecture is illustrated in Fig. 9.

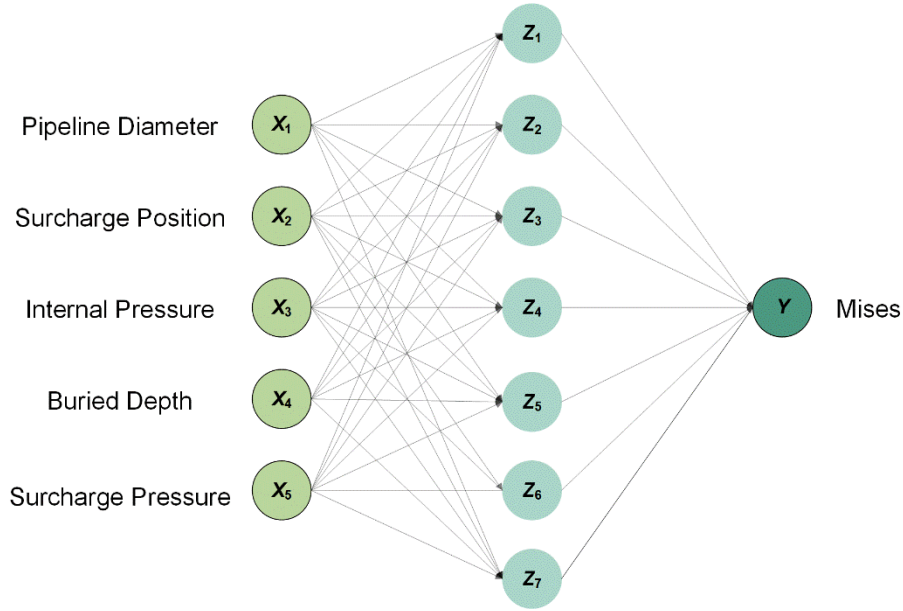


Fig. 9. Architecture of the neural network

3.2 Training and Validation of the Neural Network Model

Latin hypercube sampling was employed to generate the dataset. Pipeline diameter, surcharge position, internal pressure, burial depth, and surcharge pressure were selected as the input variables, whereas the maximum von Mises stress obtained from the finite element simulations was used as the output variable. A total of 100 samples were generated, of which 80 were used for model training and 20 for evaluating the generalization performance. The samples were divided into training and test sets using stratified random sampling.

The predictive accuracy of the model was evaluated using four statistical metrics: root mean square error (RMSE), coefficient of determination (R^2), mean absolute error (MAE), and mean bias error (MBE), as defined in Eqs. (2)–(5):

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (2)$$

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (3)$$

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (4)$$

$$\text{MBE} = \frac{1}{n} \sum_{i=1}^n (\hat{y}_i - y_i) \quad (5)$$

where n is the number of samples, y_i is the simulated value, and $\hat{y}_i$ is the predicted value, $\bar{y}$ is the average of the predicted values of all samples.

Table 3. Comparison of the predictive performance of the GA-BP and SVM models

RMSE		R^2		MAE		MBE	
GA-BP	SVM	GA-BP	SVM	GA-BP	SVM	GA-BP	SVM
10.5775	24.7483	0.9691	0.8513	7.3607	16.9723	-0.3541	-2.6671

Compared with the SVM model, the GA-BP model demonstrated superior predictive performance across all four evaluation metrics, as summarized in Table 3. The GA-BP model achieved a coefficient of determination R^2 of 0.9691, indicating close agreement between the predicted and simulated values, whereas the corresponding value for the SVM model was only 0.8513. In addition, the RMSE and MAE of the GA-BP model were reduced to 10.5775 and 7.3607, respectively, compared with 24.7483 and 16.9723 for the SVM model.

After 42 generations of optimization, the fitness value converged rapidly and stably to approximately 0.035, indicating that the genetic algorithm effectively optimized the initial network parameters, result is presented in Fig. 10. The prediction results for the training and test sets are presented in Figs. 11 and 12, respectively. Across the entire data range, the predicted values agreed closely with the numerical simulation results, including regions characterized by pronounced fluctuations and extreme values. Overall, the training and validation results indicate that the GA-BP model provides good generalization performance and prediction robustness and is capable of supporting

high-accuracy stress prediction for practical engineering applications.

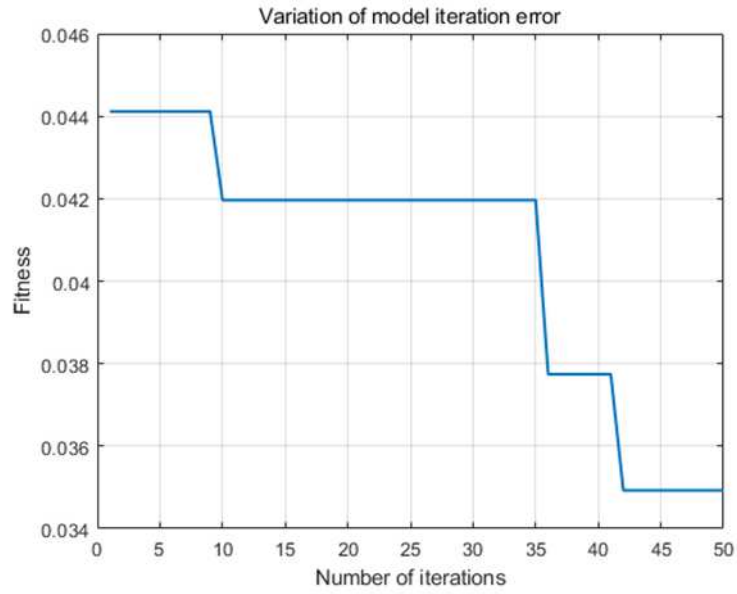


Fig. 10. Fitness convergence curve

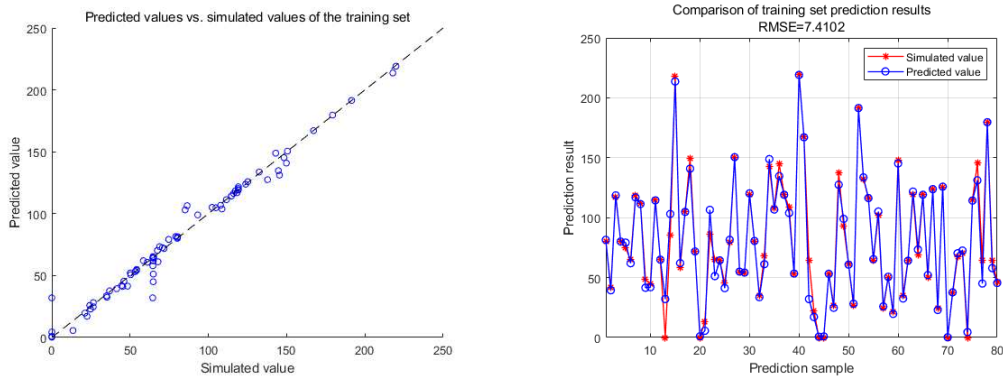


Fig. 11. Prediction results for the training set

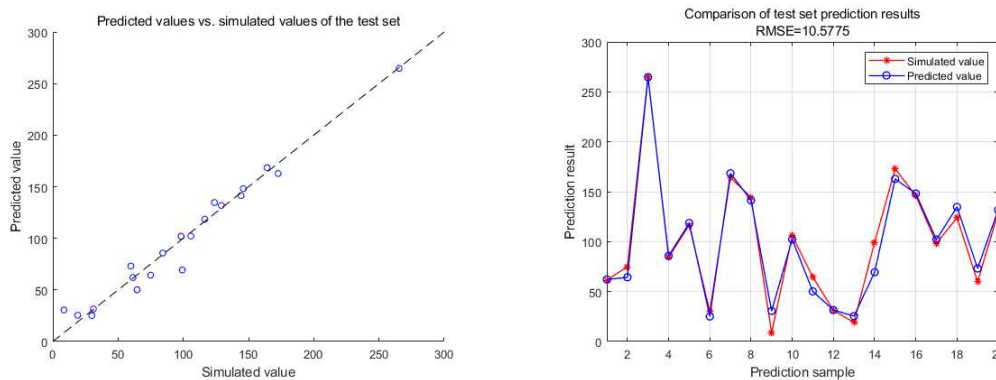


Fig. 12. Prediction results for the test set

3.3 Application of the Neural Network Model

According to GB 50251-2015, *Code for Design of Gas Transmission Pipeline Engineering* [25], the location classification and corresponding strength design factor

(F) were determined for each pipeline section, as summarized in Table 4. A failure criterion was then established based on the von Mises yield criterion, as expressed in Eqs. (6) and (7).

$$\sigma_{Allow} = \sigma_{Yield} \times F \quad (6)$$

$$\sigma_{Mises} = \sqrt{\frac{1}{2}[(\sigma_1 - \sigma_2)^2 + (\sigma_2 - \sigma_3)^2 + (\sigma_3 - \sigma_1)^2]} < \sigma_{Allow} \quad (7)$$

Where σ_{Allow} is the maximum allowable stress level during the service life of the pipeline. σ_{Yield} is the critical stress value at which the pipe material begins to undergo permanent plastic deformation, F is a coefficient used to provide a safety margin, in this study, $F = 0.6$, σ_1 , σ_2 , σ_3 are the first, second, and third principal stresses.

The assessment procedure is as follows. First, σ_{Allow} is determined according to the pipeline location classification and pipe material properties. Because the internal pressure may fluctuate during pipeline operation, pipeline safety should be reassessed according to the actual operating pressure and surcharge pressure. The detailed assessment procedure is shown in Fig. 13. Based on the developed prediction model, three-dimensional maximum-stress contour plots were further generated, enabling rapid evaluation of pipeline stress under different combinations of internal pressure and surcharge pressure.

Table 4. Strength design factors for different pipeline location classifications

Pipeline	Location classification			
	I	II	III	IV
Strength design factor(F)	0.72	0.6	0.5	0.4

Table 5. Basic parameters of three pipelines

Pipeline	Diameter(mm)	Surcharge Pressure(MPa)	Internal pressure(MPa)	Buried depth(m)	Area classification
1	406.4	0~0.4	2~8	2	II
2	273	0~0.4	2~8	1	II
3	406.4	0~0.4	2~8	1	II

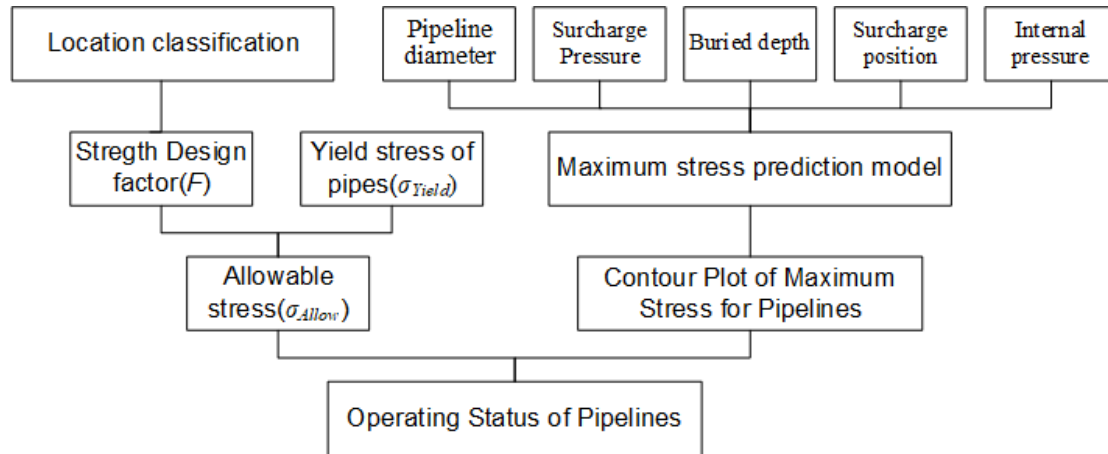


Fig.13. Assessment Process for Pipeline Safety

To demonstrate the engineering applicability of the proposed method, three pipelines exposed to potential construction surcharge risks in the Penglai Dengying Block were selected for analysis. Their basic parameters are listed in Table 5, and their field locations are shown in Fig. 14. All three locations were classified as Class II areas. Accordingly, the strength design factor was taken as 0.6. With a pipeline yield strength of 360 MPa, $\sigma_{Allow} = 216$ MPa. Maximum-stress contour plots for the three pipelines were then generated using the developed prediction model, as shown in Fig. 15.



(a) Pipeline No.1



(b) Pipeline No.2



(c) Pipeline No.3

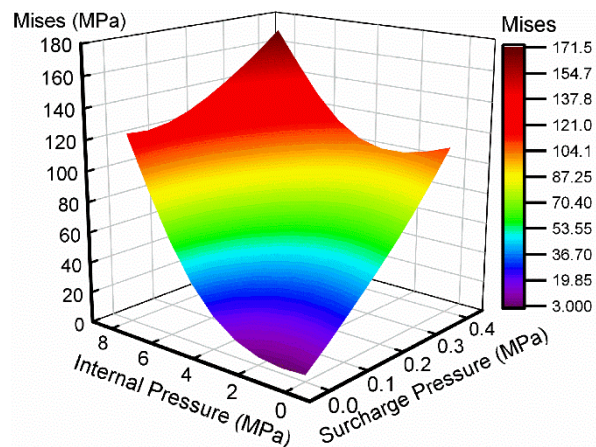
Fig. 14. Field locations of the three pipelines

The prediction results are summarized as follows:

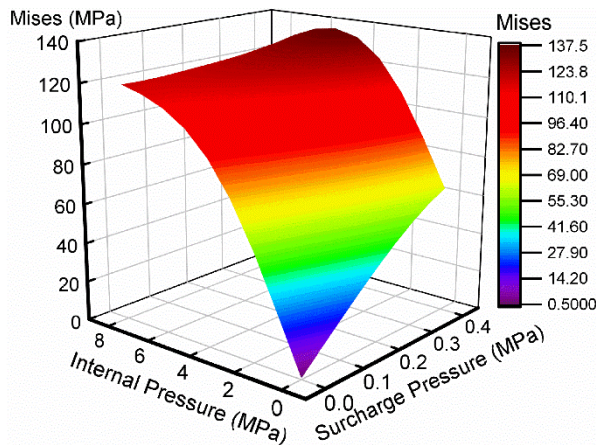
(1) Pipelines No. 1 and No. 2: Under the coupled effects of surcharge pressure ranging from 0 to 0.4 MPa and internal pressure ranging from 2 to 8 MPa, the maximum predicted von Mises stresses of Pipelines No. 1 and No. 2 were 171.06 and 137.05 MPa, respectively. Both values remained below the allowable stress of 216 MPa, indicating that the two pipelines remained within the allowable operating range under the investigated loading conditions.

(2) Pipeline No. 3: For Pipeline No. 3, the predicted peak stress under the coupled

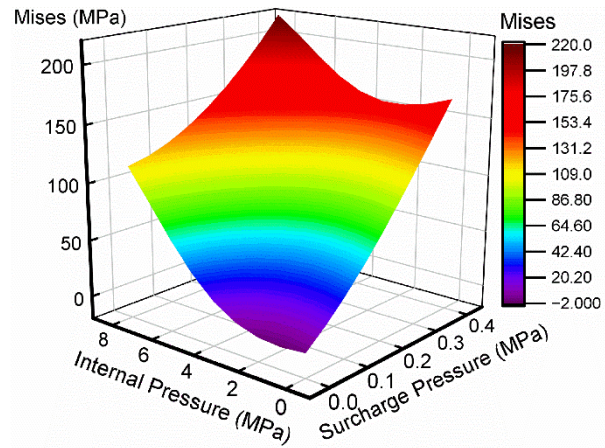
action of surcharge loading and internal pressure reached 219.11 MPa when the surcharge pressure was 0.4 MPa and the internal pressure was 8 MPa. This value exceeded the allowable stress of 216 MPa, indicating a potential failure risk under this loading condition. According to the original analysis, this relatively high stress response is primarily associated with the shallow burial depth of 1 m and the relatively large pipe diameter of 406.4 mm. Therefore, surcharge loading at and above the investigated upper level should be restricted in the vicinity of Pipeline No. 3, and appropriate engineering reinforcement measures should be implemented.



(a) Contour plot of Maximum Stress for Pipeline No.1



(b) Contour plot of Maximum Stress for Pipeline No.2



(c) Contour plot of Maximum Stress for Pipeline No.3

Fig. 15. Contour plots of Maximum Stress for three pipelines

4. Conclusions

In this study, finite element numerical simulations combined with machine-learning algorithms were employed to investigate the mechanical response mechanisms of buried pipelines subjected to surcharge loading. The mechanical response characteristics of pipelines under multiple influencing factors were quantitatively analyzed, and a GA-BP neural network-based prediction model for the maximum pipeline stress was developed. The main conclusions are summarized as follows:

(1) A three-dimensional finite element model incorporating pipe–soil interaction was established using ABAQUS. The simulation results showed good agreement with experimental data, with a mean error of 6.32% for the predicted von Mises stress. The developed model can accurately reproduce the mechanical response characteristics of buried natural gas pipelines subjected to surcharge loading.

(2) Under construction surcharge loading, the pipeline stress distribution varied significantly within the directly affected surcharge region and exhibited a symmetric double-peak pattern. The maximum von Mises stress occurred at the bottom of the pipeline.

(3) A GA-BP neural network model was developed to predict the maximum von Mises stress of buried pipelines. The model achieved an R^2 value of 0.9691, demonstrating satisfactory predictive performance, providing an efficient approach for rapid integrity assessment of pipelines subjected to construction surcharge loading.

(4) Based on the prediction model, three-dimensional contour maps of the maximum pipeline von Mises stress under different operating conditions were generated. The proposed framework was applied to evaluate three in-service crossing pipelines, and the results indicated that Pipeline No. 3 was associated with a potential

failure risk.

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Author contributions

Lin Chen: Writing – review & editing, Methodology, Software, Validation, Formal analysis. **Yabo Lü:** Project administration, Conceptualization, Methodology, Resources. **Liyuan Guo:** Writing-original draft, Software, Formal analysis, Visualization. **Jiaqiang Ou:** Supervision, Writing – review & editing, Validation. **Wu Liu:** Funding acquisition, Resources, Project administration. **Hongtao Xiao:** Investigation, Data curation, Validation, Visualization. All authors reviewed and approved the final manuscript.

Competing interests

The authors declare no competing interests.

Data availability

The datasets generated and/or analyzed during the current study are available from the corresponding author on reasonable request.

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