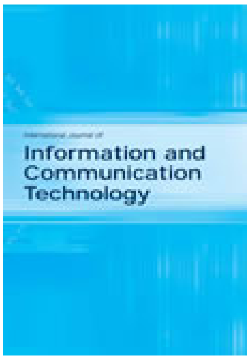

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Early warning and decision-making model of geological disaster damage of transmission lines based on intelligent online monitoring technology

Yong Yang, Xiaoqin Zhu, Xi Song, Hehui Zhang, Xun Zhang

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Early warning and decision-making model of geological disaster damage of transmission lines based on intelligent online monitoring technology

Yong Yang and Xiaoqin Zhu*

State Grid Gansu Electric Power Research Institute,
Lanzhou, China
Email: 283812390@qq.com
Email: fusion081001@163.com
*Corresponding author

Xi Song

State Grid Gansu Electric Power Company,
Lanzhou, China
Email: songxi_sgcc@163.com

Hehui Zhang and Xun Zhang

State Grid Gansu Electric Power Research Institute,
Lanzhou, China
Email: zhh950620@163.com
Email: zhangxunsf@qq.com

Abstract: In adverse weather conditions, using the naked eye or actual measurement to determine the abnormal situation of transmission lines can accumulate a large amount of data and experience in manual measurement. In order to improve the operational stability of transmission lines, this paper proposes a dictionary learning based dance reconstruction method for transmission lines. The transmission lines are treated as curves in three dimensional spaces and the sparsity of dancing wires is analysed. The points on the transmission lines are treated as three-dimensional coordinate points, and the dance information of the transmission lines is analysed. Through the analysis of experimental results, it can be seen that the acceleration and angular velocity errors caused by geological disasters detected by the intelligent online monitoring technology model proposed in this paper are within a reasonable range, and reliable decision-making suggestions can be made after geological disasters occur.

Keywords: online monitoring; transmission line; geological disasters; early warning; decision-making.

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Biographical notes: Yong Yang obtained a Master's in Electronic and Communication Engineering from Lanzhou University and currently works at State Grid Gansu Electric Power Research Institute, with a research focus on power communication technology.

Xiaoqin Zhu obtained a Master's in Communication and Information Systems from Lanzhou University of Technology and currently works at State Grid Gansu Electric Power Research Institute, with a research focus on power communication technology.

Xi Song obtained a Master's in Optical Information Communication from Lanzhou University and currently works at State Grid Gansu Electric Power Company, with a research focus on power communication technology.

Hehui Zhang obtained a Master's in Control Theory and Control Engineering from Lanzhou University of Technology and currently works at State Grid Gansu Electric Power Research Institute, with a research focus on power communication technology.

Xun Zhang obtained a Master's in Electrical Engineering and Automation from Xi'an Jiaotong University and currently works at State Grid Gansu Electric Power Research Institute, with a research focus on power communication technology.

1 Introduction

With the increasingly perfect power grid structure and the continuous improvement of power grid management level, the safety and stability level of the power system has also greatly improved. However, power grid accidents caused by natural disasters such as thunderstorms and icing still occur from time to time, and the consequences of serious natural disasters cannot be ignored. In recent years, severe thunderstorms, icing and other disasters have caused large-scale power outages in many areas, and the grid structure has been severely damaged, which has sounded the alarm for potential crises for us. In response to various natural disasters such as thunderstorms and icing, relevant departments are actively seeking effective methods to forecast and warn meteorological disasters. A complete meteorological disaster early warning system needs to be composed of monitoring, early warning, and information dissemination. A lot of beneficial explorations have been made in meteorological disaster warning, power grid operation monitoring, and fault repair optimisation, greatly promoting production. Mainly relying on modern information technology, adopting more effective disaster prediction and monitoring technologies, efficiently utilising and integrating limited resources, and improving the risk response and emergency response capabilities of ultra-high voltage transmission channels. Research on transmission lines and meteorological conditions analysis has been carried out in developed coastal areas, and related service systems, warning and forecasting systems are gradually being established and improved. However, in the research of power grid disaster warning, the research on unique disasters of ultra-high voltage channel power grids in specific environments (such as thunderstorms and icing) tends to be vague and has average timeliness. Most of the research focuses on the state of the power grid itself or simply uses the disaster prediction data provided by meteorological departments. The combination of the two methods is relatively single and not conducive to overall statistical evaluation. Although some research has also mentioned the importance of non-grid information for grid safety risk warning research, due to its immeasurability, there has not been a systematic study, and a monitoring, analysis, and warning model suitable for specific disasters in ultra-high voltage transmission channels has not been established. The above defects make the current power grid meteorological disaster monitoring and early warning system only capable of preliminary monitoring, analysis, and early warning, rather than precise analysis and early warning.

The safety and stability of transmission lines directly determine the quality of life of ordinary people. Moreover, transmission lines are mostly located in complex environmental areas, the probability of geological disasters is high, and the maintenance of transmission lines is difficult, so it is particularly important to detect and warn transmission line disasters in advance.

In recent years, with the development of computer vision technology, many researchers have applied computer vision technology to the field of transmission line security. Du et al. (2023) proposes to evaluate the protective performance of metal oxide lightning arresters on transmission lines based on artificial intelligence technology, and conducts research on the research status and development trends of transmission line inspection robots. At present, research on the intelligent video warning system for preventing external damage of transmission lines is increasing, mainly focusing on two aspects. Firstly, the hardware scheme design of the warning system, such as power supply scheme, communication network scheme, etc. The second warning system software scheme design includes system requirement analysis, system functions, and implementation algorithms. As mentioned earlier, the collision of large robotic arms with transmission lines accounts for a high proportion of external damage factors and poses significant risks. Therefore, many researchers have conducted research specifically on early warning systems for large robotic arms invading transmission lines. Yang et al. (2020) proposes to divide the early warning system into front-end monitoring system and back-end service system. The front-end detection system realises image acquisition and analysis, while the back-end service system realises monitoring service and management. It also proposes an anti external breach system that combines video detection technology and radar detection technology.

In terms of motion object detection, Butsykin et al. (2023) proposed an improved update strategy for the single Gaussian background modelling method based on the number of foreground counts to determine whether to update foreground points. This has to some extent improved the problem of the front attraction being mistakenly identified as the front attraction when it has already been integrated into the background, but still does not solve the problem of the single Gaussian background modelling method being susceptible to light and small disturbances; Nirmal (2020) proposes object detection based on multi-Gaussian background modelling, which to some extent improves the ability to adapt to the environment, but the algorithm complexity increases and real-time performance decreases. In terms of motion target recognition, some literature proposes training support vector machines based on features such as area, eccentricity, and compactness to achieve recognition. In terms of motion target tracking, Coletta et al. (2020) proposes using the Camshift algorithm to fuse a Kalman filter to predict target positions, which can improve the tracking accuracy of the Camshift algorithm while maintaining high prediction accuracy. The prediction accuracy of the Kalman filter is closely related to the establishment of the state equation. In the actual tracking process of the boom, the state equation is established based on the boom motion state. In terms of warning algorithms, Datta et al. (2023) proposes a warning algorithm based on the angle of the lifting arm, which does not consider the relative position between the transmission line and the lifting arm. However, there are limitations in practical application. Someone has proposed using binocular stereo vision to calculate the distance between the transmission line and the crane arm, and further warning based on the distance. However, this algorithm does not perform stereo correction before stereo matching, resulting in low search efficiency and large matching errors during the matching process.

There are three main types of geological prediction models for transmission lines based on statistical methods: the first type calculates the frequency of geological disasters in transmission lines through historical geological data, and estimates the recurrence period of geological disasters from this; the second type of model predicts the geological thickness of transmission lines by analysing time series; the third type of model uses mathematical statistical methods to calculate the linear relationship between factors such as temperature, air pressure, wind speed, wind direction and relative humidity, as well as wire tension, and the geological thickness of the transmission line. Based on the obtained rules, it predicts the geological thickness of the transmission line (Kong and Song, 2022). The recurrence period of geological hazards in transmission lines refers to the average interval between the occurrence of a hazard greater than or equal to a certain geological intensity. Geological disasters in transmission lines are similar to other disasters, and the occurrence of major geological disasters is a low probability event. The more severe the disaster, the further away it will be from the next disaster. If there is sufficient historical geological data, the recurrence period of geological hazards in transmission lines can be calculated using probability models, with the commonly used model being the extremum model (Zhou et al., 2020). Liu et al. (2020) used the maximum geological thickness to construct a fuzzy Markov chain model for predicting the annual geological conditions in the next year or several years, with a prediction accuracy of 80%; Liu et al. (2021) improved the geological time series prediction model for transmission lines using the fireworks algorithm, with an average error of 2.67%, which is much better than the ordinary model; Khan et al. (2019) optimised the hyperparameters of the prediction model based on autoregressive integral moving average model using genetic algorithm, and combined with Kalman filtering algorithm, the accuracy of the model was significantly improved. The formation of geological conditions in transmission lines is closely related to meteorological conditions and equipment parameters (such as the tension of wires and the wind deflection angle of insulators), and considering these influencing factors can provide a more accurate estimation of geological conditions in transmission lines. Shu and Zheng (2020) used meteorological observation data from geological sites and IRM signals representing geological development stages to construct a linear model for predicting the geology of transmission lines, and obtained good prediction results. By analysing online meteorological observation data and geological observation data of transmission lines, it is pointed out that only geology formed during prolonged low-temperature rainy and snowy weather will have an impact on the normal operation of transmission lines; the weight of geological growth per unit time is approximately normally distributed; there is a strong linear function relationship between geological quality and time during the process of stable geological growth. Jiang et al. (2022) uses meteorological factors such as temperature, air pressure, wind speed, and relative humidity to predict the geology of transmission lines. It is proposed that when the prediction accuracy of the geological model of transmission lines decreases due to data reasons, a fuzzy Markov chain model can be used to modify the original model. The prediction error of the model is significantly reduced compared to the geological thickness growth model. However, these geological prediction models for transmission lines based on statistical methods also have many shortcomings. The models used for geological prediction of transmission lines using mathematical statistical methods, such as meteorological factors and wire tension, are relatively simple linear models and cannot learn the nonlinear influencing factors. Meanwhile, due to the fact that factors such as wire tension can only be obtained through real-time observation, it is not possible to truly predict the geological conditions of future transmission lines.

The geological values obtained by the geological monitoring system during blizzard weather are not very accurate, so it is necessary to accurately predict the geological thickness of transmission lines in real time. In previous research, real-time meteorological observation data and mechanical data such as real-time monitoring of wire tension are usually used as input data for machine learning models to predict the geological thickness of transmission lines in real time. Due to the impact of data pre-processing on model performance, more and more scholars have adopted appropriate pre-processing schemes before modelling in recent years in order to obtain more accurate geological prediction results of transmission lines. Vlahinić et al. (2020) used the integrated empirical mode decomposition method to adaptively decompose meteorological data and equipment parameters, which can fully extract the time series information contained in the data. After processing the data, it was fed into support vector machines, backpropagation neural networks (BPNN), and random forest models, and the predictive ability of the models was significantly improved. Li and Qi (2022) used principal component analysis, local binary mode, and relief feature selection methods to extract features from heterogeneous data such as meteorological elements, equipment parameters, and geological image data. Then, an extreme learning machine model was constructed based on radial basis function kernels, and accurate geological thickness prediction results were obtained. Chawla et al. (2023) used parallel coordinate systems to convert multidimensional data into images, and then used convolutional neural network (CNN) to predict the geology of transmission lines. However, due to the presence of real-time monitoring mechanical data such as wire tension in the input data, which is different from meteorological factors, the mechanical data obtained from such real-time monitoring cannot be predicted in advance. Therefore, this type of transmission line prediction model can only be used for real-time geological observation and cannot be used to predict the future geological thickness of transmission lines.

Ragusa et al. (2021) used the K-means algorithm to filter geological historical data, and then used the least squares support vector machine for modelling, obtaining a transmission line geological model with strong generalisation ability and relatively accuracy. Several simple machine learning algorithms similar to support vector machines were used as weak learners to model the relationship between meteorological elements and transmission line geology. After integrating these weak learners using adaptive boosting (AdaBoost) algorithm, the prediction accuracy of the model was significantly improved. However, with the rise of the wave of machine learning applications, more and more scholars are beginning to attempt to use more complex machine learning algorithms for modelling. For more complex machine learning models, especially neural network models, hyperparameters have a significant impact on the performance of the model. Therefore, previous researchers have attempted various optimisation algorithms to tune hyperparameters. Rexhepi and Hulaj (2020) combined genetic algorithm and taboo search algorithm to search for the optimal hyperparameters for support vector machine based models, and the performance of the model was significantly improved after optimising the hyperparameters. Similarly, Palangar et al. (2021) used the fruit fly optimisation algorithm (FOA) to optimise the hyperparameters of the general regression neural network (GRNN), and selected features using the data inconsistency rate (IR) to construct the FOA-IR-GRNN model. Sufyan et al. (2021) used the grey correlation analysis method to calculate the grey correlation relationship between geological thickness and various meteorological elements. Based on this, a multivariate grey model and a BPNN transmission line geological prediction model were constructed, and a geological hazard risk map was drawn using a GIS system. Ghosh and Chatterjee (2021) used the chaotic grey wolf optimisation algorithm to optimise the parameters of the extreme learning machine, and the model also has good predictive performance. According to the characteristics of geology, geological processes are divided into three stages: rapid growth, stable growth, and geological melting. Then, extreme learning machines are used to predict geology at different stages, and the bat algorithm is used to optimise the model. The resulting mixed model has higher predictive performance. After constructing an offline support vector machine geological prediction model for transmission lines in Ding et al. (2020), an online support vector algorithm was used to dynamically adjust the weight coefficients of the samples, resulting in an online prediction model driven by on-site observation data.

Under the influence of wind, the ice covered transmission line will experience horizontal, vertical, and longitudinal oscillations due to the unbalanced force on the conductors. When the dance reaches a certain stage, not only will the transmission line be pulled or broken, but the transmission tower will also collapse as a result, causing huge losses. At present, most of the research on the dancing characteristics of transmission lines uses fluid software such as Fluent and ANSYS to simulate the real climate environment and analyse the aerodynamic parameters of single point transmission lines under different wind speeds, angles of attack, and ice thickness. However, such methods cannot observe the dancing situation of the entire transmission line, so their limitations are too strong. This article regards wire dancing signals as three-dimensional data containing spatial and temporal information. Starting from the characteristics of dancing wires, the sparsity of wire dancing signals in the time and spatial domains is analysed. Due to the diverse postures of wire dancing and the real-time changes that occur with the environment and temperature, this paper abandons the existing sparse basis based on the principle of compressive sensing, and uses dictionary learning to find suitable sparse basis for real-time reconstruction of the dancing curve. Combined with intelligent systems for real-time monitoring, it effectively improves the detection effect of the actual situation of transmission lines after geological disasters

The ultra wideband positioning technology and compressive sensing principle are in full swing. This paper combines ultra wideband technology with compressive sensing principle to achieve online monitoring of transmission line dancing. By using ultra wideband positioning technology to obtain the three-dimensional coordinates of points along the transmission line, combined with the sparsity of transmission line dancing signals in time, space, and other joint domains, the characteristics of transmission line dancing are searched for, and the mapping relationship between the dancing signal and the measured three-dimensional coordinates is constructed. Finally, the original signal is restored from the measurement data through reconstruction algorithms. On the one hand, it saves a lot of manpower and material costs to ensure the safe operation of transmission lines; On the other hand, through online monitoring, the amplitude and half wave number of transmission line dancing can be monitored in real time, providing early warning effects for workers to prevent and control, and also facilitating the verification of anti dancing equipment effectiveness by the power department in the later stage. Therefore, online monitoring of transmission line dancing is of great significance for ensuring the safe operation of transmission line systems.

To cope with various geological and natural disasters, it is necessary to actively seek effective methods to forecast and warn meteorological disasters. A complete meteorological disaster early warning system needs to be composed of monitoring, early warning, and information dissemination. The goal of this article is to construct a transmission line early warning decision model suitable for geological disasters and improve the stability of transmission lines.

Design dedicated data acquisition modules, data transmission modules, and energy modules to achieve monitoring and wireless transmission of transmission towers and environmental parameters; Develop server programs to manage monitoring data, calculate and predict the safety status of power towers, and analyse early warnings; Develop a user end to provide data query, warning information transmission, and communication services for users at all levels, and basically achieve safe operation warning and decision-making of transmission line towers in the event of geological disasters

In order to improve the early warning effect of geological disaster damage of transmission lines, this paper combines with intelligent on-line monitoring technology to build an early warning decision model of geological disaster damage of transmission lines based on intelligent on-line monitoring technology, and use simulation form to verify the effect of the early warning decision model of geological disaster damage of transmission lines.

2 Detection algorithm of transmission line galloping

Under the influence of geological disasters, transmission lines will gallop in three directions: horizontal, vertical and longitudinal due to the unbalanced stress of conductors under the action of external forces. When the galloping reaches a certain stage, not only the transmission line will be pulled and broken, but also the line tower will collapse, causing huge losses. At present, most of the researches on the galloping characteristics of transmission lines use Fluent, ANSYS and other fluid software to simulate the real climate environment, and analyse the aerodynamic parameters of single-point transmission lines under different wind speed, angle of attack and ice thickness. However, such methods cannot observe the galloping situation of the whole transmission line, so their limitations are too strong.

Most overhead transmission line suspension methods are mainly divided into two types, namely, equal height suspension and unequal height suspension. When the wire is at rest, it can be equated with the quadratic function in two-dimensional space. At present, the distance between the two suspension points of the conductor is relatively long, and the influence of the rigid material of the conductor on the geometric shape of the conductor suspended in the air is negligible. That is to say, it can be assumed that the conductor is a flexible chain hinged everywhere, and the conductor mass is evenly distributed along the conductor direction, so the catenary equation of overhead transmission line can be obtained in this case (Khan et al., 2022a):

$$z(x) = x \tan \beta - \frac{Wx(l-x)}{2T_0 \cos \beta} \tag{1}$$

Among them, $z(x)$ is the ordinate of any point on the conductor before galloping, β is the height difference angle of the suspension point, W is the unit length of the iced conductor, l is the distance between the suspension points, T_0 is the horizontal tension of the conductor. When $h_{AB} = 0$, $\beta = 0$, and the wires are in the same height suspension mode. When $h_{AB} \neq 0$, the wires are suspended in unequal height.

Conductor shape with unequal height at suspension point as shown in Figure 1. Traverse galloping signals can be considered as three-dimensional data, which contains information in time dimension and space dimension. Starting from time domain, because galloping is low frequency, galloping signals have strong correlation in adjacent time, that is to say, there is information redundancy between signals at adjacent time points. Starting from airspace, because the conductor is made of rigid material, there are certain constraint characteristics between adjacent two points. Figures 2(a) and 2(b) show the vertical data matrix and horizontal data matrix when the conductor gallops respectively. It can be seen from the figure that there are few characteristics of conductor galloping in both vertical and horizontal directions, and they are relatively fixed. If the appropriate sparse basis is used to extract all the features on the image, the galloping signal will show good sparsity on this sparse basis.

Figure 1 Conductor shape with unequal height at suspension point (see online version for colours)

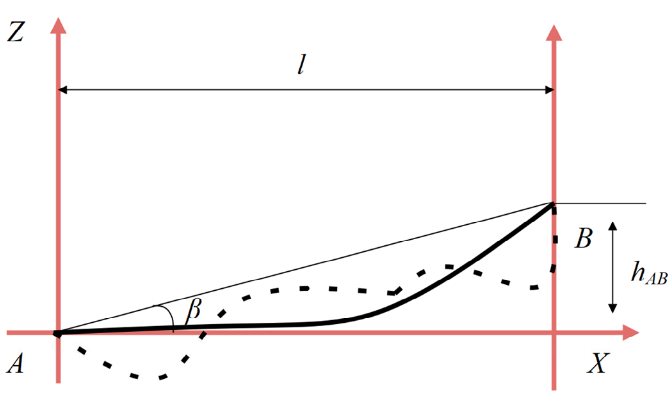
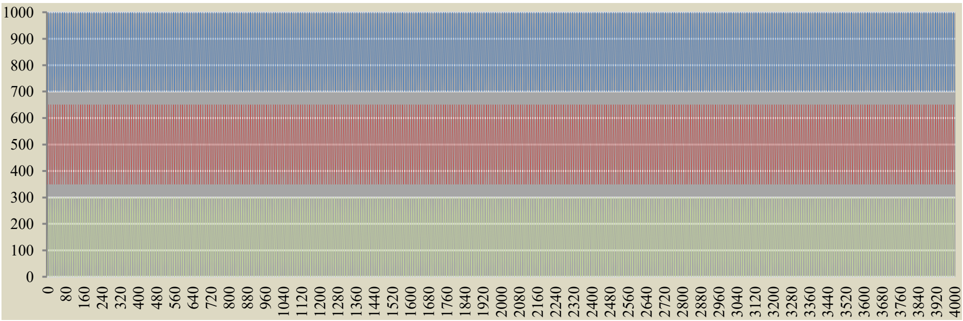
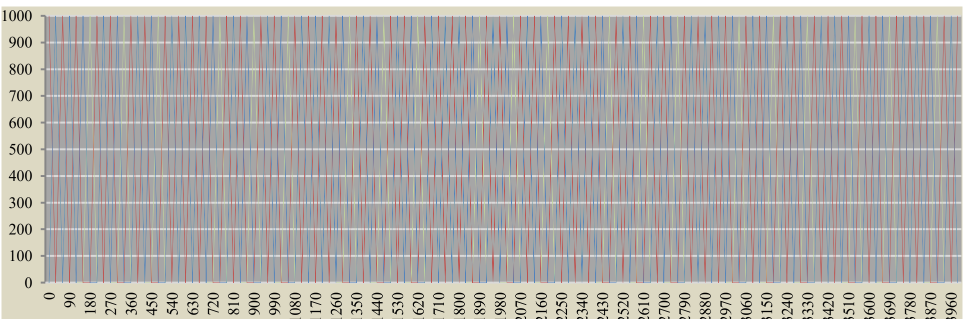


Figure 2 Galloping conductor, (a) vertical vibration of galloping conductors (b) horizontal vibration of galloping conductors (see online version for colours)

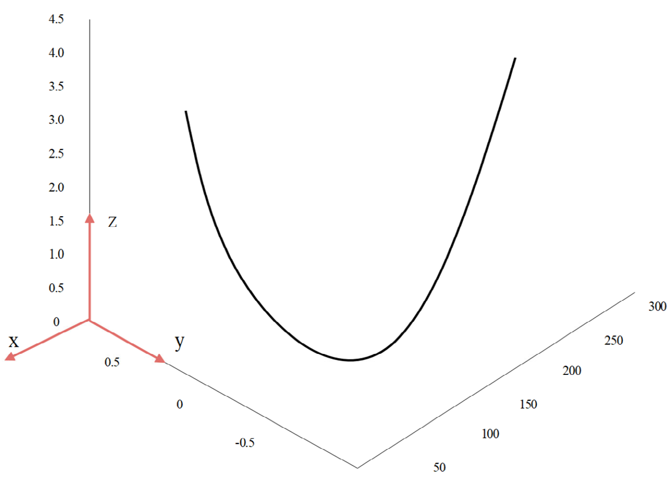


(a)



(b)

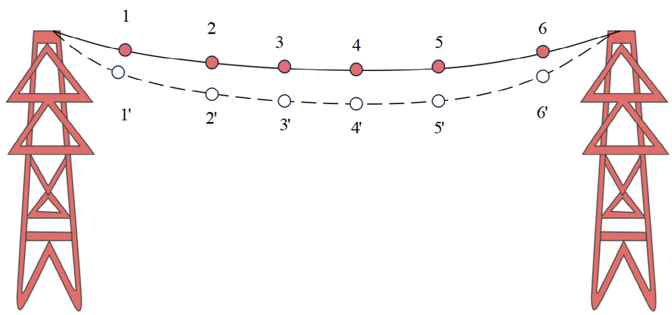
Figure 3 Curves in three-dimensional space (see online version for colours)



In order to use the principle of compressed sensing, we regard the wire as a curve in Cartesian coordinate system. Under this model, whether the wire is galloping or stationary, the wire can find its corresponding curve in the coordinate system, and every point on the wire can find its position in the coordinate system, as shown in Figure 3 (Khan et al., 2022b).

In the aspect of obtaining the position information of each point on the wire, combined with Chan algorithm, this paper uses TDOA-based ultra-wideband positioning technology to arrange several tags along the wire, and obtains the position information of the wire galloping by calculating the distance difference between the tags and the surrounding base stations. The installation diagram of the tags is shown in Figure 4. The calculation of tag position and the hardware design of UWB positioning system are all undertaken by other members of the research group.

Figure 4 Schematic diagram of UWB positioning (see online version for colours)



We assume that N_l tags are installed along the wire, and the coordinates of each tag l_i are expressed as (x_i, y_i, z_i), where $i \in [1, N_l]$. In time T, if the position information of the tag on the wire is measured at time intervals Δt, $N_t \times N_l$ measured values can be obtained, where $N_t = \frac{T}{\Delta t}$. When the measured values are expressed by matrix L, the following results are obtained (Khan et al., 2023):

$$L = \begin{bmatrix} l_{1,1} & l_{1,2} & \cdots & l_{1,Nt} \\ l_{2,1} & l_{2,2} & \cdots & l_{2,Nt} \\ \cdots & \cdots & \cdots & \cdots \\ l_{N1,1} & l_{N1,2} & \cdots & l_{N1,Nt} \end{bmatrix} \tag{2}$$

Among them, each row in matrix L represents all measurements of labels in time T, and each column represents the positions of all labels of the whole wire at a certain point in time. Moreover, each element of L is a three-dimensional coordinate. Because the coordinate axes are orthogonal and have no corresponding connection, the data of each axis can be extracted from the coordinates and processed one by one when analysing the data. For example, the data on the axis X can be expressed as follows (Khan et al., 2022c):

$$X = \begin{bmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,Nt} \\ x_{2,1} & x_{2,2} & \cdots & x_{2,Nt} \\ \cdots & \cdots & \cdots & \cdots \\ x_{N1,1} & x_{N1,2} & \cdots & x_{N1,Nt} \end{bmatrix} \tag{3}$$

Under the compressed sensing framework, the sampled galloping signal g can be expressed by the following equation (Khan et al., 2022d):

$$g = \Phi f \tag{4}$$

In equation (4), $f \in \mathbb{R}^N$ represents the original galloping signal, $\Phi \in \mathbb{R}^{M \times N}$ represents the sampling matrix, which consists of digits 0 and 1, where 0 represents unsampled points, 1 represents sampled points, and $g \in \mathbb{R}^M$ represents the actually acquired incomplete galloping signal. When the original galloping signal f exhibits sparse characteristics in the sparse dictionary $D(f = Dw)$, the sampled signal g may be expressed as (Bilal et al., 2024a):

$$g = \Phi f = \Phi D w = \Theta w \tag{5}$$

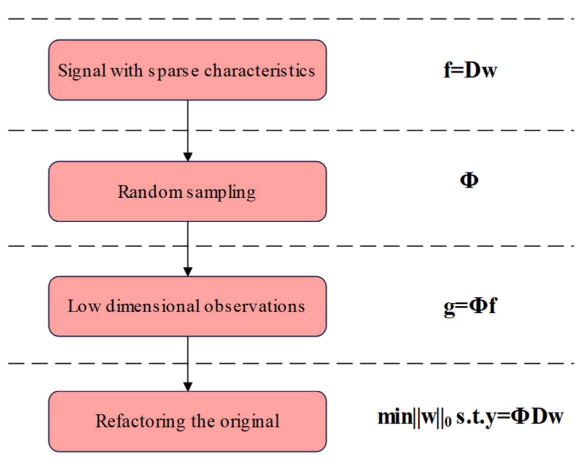
In the sampling matrix Φ, $M < N$, that is, the number of unknowns is greater than the number of equations. This is an uncertain problem, but due to the sparsity of $w = D^H f$, the original reconstruction problem can be simplified to (Bilal et al., 2024b):

$$\min \|w\|_0 \text{ s.t. } g = \Theta w \textit{ there is no noise in the measured values} \tag{6}$$

$$\min \|w\|_0 \text{ s.t. } \|\Theta w - g\| \le \varepsilon \textit{ there is noise in the measured value} \tag{7}$$

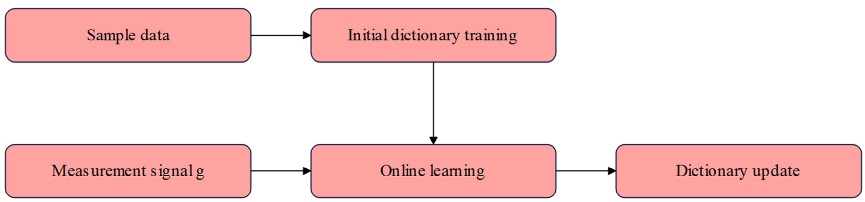
The theoretical framework of galloping curve reconstruction based on compressed sensing can be used in Figure 5, which can be divided into three steps: sparse representation, signal measurement and signal reconstruction.

Figure 5 Reconstruction model of galloping curve (see online version for colours)



By training the sample signal, the dictionary will contain most of the features of the original signal, and the more information the sample signal contains, the stronger the sparse representation ability of the dictionary. Therefore, the sample data is obtained by Simulink simulation, and the feature extraction of the sample data is carried out to obtain the initial dictionary. On the one hand, because the data obtained by the model is ideal, there are still many deviations from the actual measured signals. On the other hand, the parameters of galloping environment, such as wind speed, ice thickness and temperature, are so varied that the original dictionary obtained by K-SVD cannot include all galloping characteristics. In order to respond to the signal changes in real time and adjust the mismatch state of the dictionary, online dictionary learning method is needed to modify the initial dictionary according to the measured signal. The algorithm block diagram is in Figure 6.

Figure 6 Dictionary learning algorithm framework (see online version for colours)



In the initial stage, the sample data are trained by K-SVD. The basic idea of K-SVD algorithm is to consider the contribution of the dictionary column vectors to signal fitting one by one and update the dictionary column vectors one by one. Moreover, K-SVD algorithm can be regarded as a special K-means algorithm. Similarly, in the iterative steps of K-means, K subsets are calculated, and each iteration of K-SVD is also to find K submatrices. If we assume that $D \in \mathbb{R}^{N \times N}$ is the trained dictionary, $f \in \mathbb{R}^N$ is the sample signal, $w \in \mathbb{R}^N$ is the corresponding sparse vector, $F = \{f_i\}_{i=1}^N$ is the set of N sample signals and $W = \{w_i\}_{i=1}^N$ is the set of F sparse solution vectors, then the optimisation process of N dictionary learning can be expressed as follows (Bilal et al., 2023):

$$\min \|F - DW\|_F^2 \; s.t. \; \forall i \; \|w_i\|_0 \le K \tag{8}$$

K in equation (8) is the maximum of non-zero numbers in sparse coefficient. The corresponding K-SVD dictionary learning algorithm executes the following steps:

1 Initialisation: The number of iterations of the algorithm is set to $t = 0$, and the algorithm initialises the dictionary D, that is, D^0. The algorithm can select Gaussian random matrix or randomly select T samples from sample signals as initial dictionary.

2 Sparse coding stage: The number of iterations is set to $t = t + 1$. According to the dictionary D selected above, for g, an approximate solution of equation (8) is solved using a tracking algorithm to obtain a sparse coefficient matrix W^t.

$$w_i = \arg\min \left\| f_i - D^{t-1} W \right\|_2^2 \; \text{s.t.} \; \|w\|_0 \le K \tag{9}$$

3 Dictionary updating stage: The algorithm fixes the sparse coefficient vector w_i, and updates the column vector $d_j (j = 1, \ldots, M)$ in the dictionary D one by one by using the following methods, and calculates its residual matrix (Bilal et al., 2022):

$$E_j = F - \sum_{l \ne j} d_l w_T^l \tag{10}$$

In the equation, w_T^l is the l^{th} row vector of sparse coefficient matrix W^t.

We set φ_k as the set of indexes of points of $w_T^l \neq 0$, that is, $\varphi_k = \{i \mid 1 \leq i \leq k,\ w_T^l(i) \neq 0\}$. Ω_k is a matrix of $N \times |\varphi_k|$, whose value at ($\varphi_k(i)$, i) is 1 and other values are 0. If we set $E_R^k = E_k \Omega_k$ and $w_R^k = w_T^k \Omega_k$, E_R^k and w_R^k are denoted as values of E_k and w_T^k after zero input, respectively. When E_R^k is singularly decomposed (SVD), $E_R^k = U \Delta V^T$, where U and V are pairwise orthogonal matrices and Δ is diagonal matrix, the formula is as follows (Bilal et al., 2021):

$$\Delta = \begin{bmatrix} \Sigma & 0 \\ 0 & 0 \end{bmatrix} \tag{11}$$

Among them, $\Sigma = diag(\sigma_1, \sigma_2, \ldots, \sigma_r)$, and σ is all non-zero singular values in E_R^k. The dictionary column vector d_k is set as the first column vector of the matrix U and the sparse coefficient w_R^k is set as the product of the matrix V and $\Delta(1, 1)$. The dictionary D is thus updated column by column until a new dictionary is generated.

4 Loop termination: If the algorithm reaches the iteration times or the convergence condition is satisfied, the algorithm terminates the loop, otherwise it enters the next loop.

Although the dictionary obtained in the initial dictionary training stage has extracted most of the characteristics of conductor galloping signals, the conductor galloping signals are constantly changing with the changing environment. Moreover, the theoretical value can never replace the actual value, and the dictionary obtained only according to the theoretical value is difficult to adapt to various time-varying models. In order to solve the mismatch problem of the original dictionary, an online dictionary learning method is proposed, which realises the real-time update of the dictionary by adding an increment to each column of the original dictionary. The increment method is as follows:

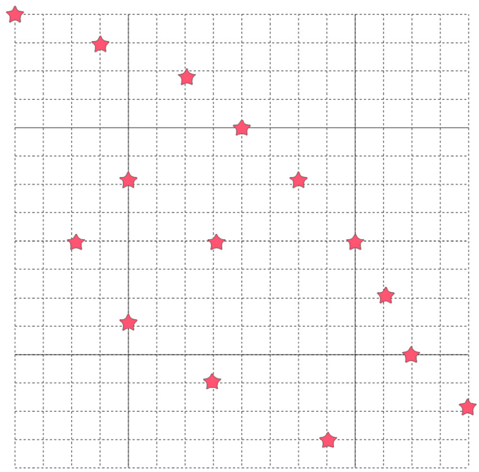
$$\begin{aligned} u_j &\leftarrow \frac{1}{A[j, j]}\left(b_j - Da_j\right) + d_j \\ d_j &\leftarrow \frac{1}{\max\left(\left\|u_j\right\|, 1\right)} u_j \end{aligned} \tag{12}$$

In equation, d_j, a_j and b_j are the j^{th} column vectors of matrices D, A_n and B_n, respectively, while A_n and B_n are the intermediate vectors in the online learning algorithm. The formula is as follows:

$$\begin{aligned} A &\leftarrow A + ww^T \\ B &\leftarrow B + fw^T \end{aligned} \tag{13}$$

The uniform sampling method is adopted here. The measurement method is to discretise the signal and represent it with L points, then divide the sampled signal into M sub-blocks, and then randomly select a point as the measurement point in each sub-block, such as $1L/M + 2$, $2L/M + 1$, $3L/M + 3$. In this way, the information is extracted for each sub-block, which keeps the integrity of the information and brings a little randomness at the same time. Taking the transmission line span length l = 1,055 m as an example, we assume that the complete information of the original signal f can be replaced by 150 points, that is, $f = [f_1, f_2, \ldots, f_{150}]$, where $f_i = [x_i, y_i, z_i]$. If these points are divided into 10 sub-blocks evenly, each sub-block has 15 points, and a point in the sub-block is selected to place labels. As shown in Figure 7, × represents the point where the point is sampled.

Figure 7 The diagram of uniform sampling distribution (see online version for colours)



The sampling matrix $\Phi \in \mathbb{R}^{10\times15}$ is represented as:

$$\Phi = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & \cdots & 0 \\ 0 & \cdots & 1 & 0 & 0 & 0 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 1 & 0 & 0 & 0 & \cdots & 0 \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & \cdots & 1 \end{bmatrix}_{10\times15} \tag{14}$$

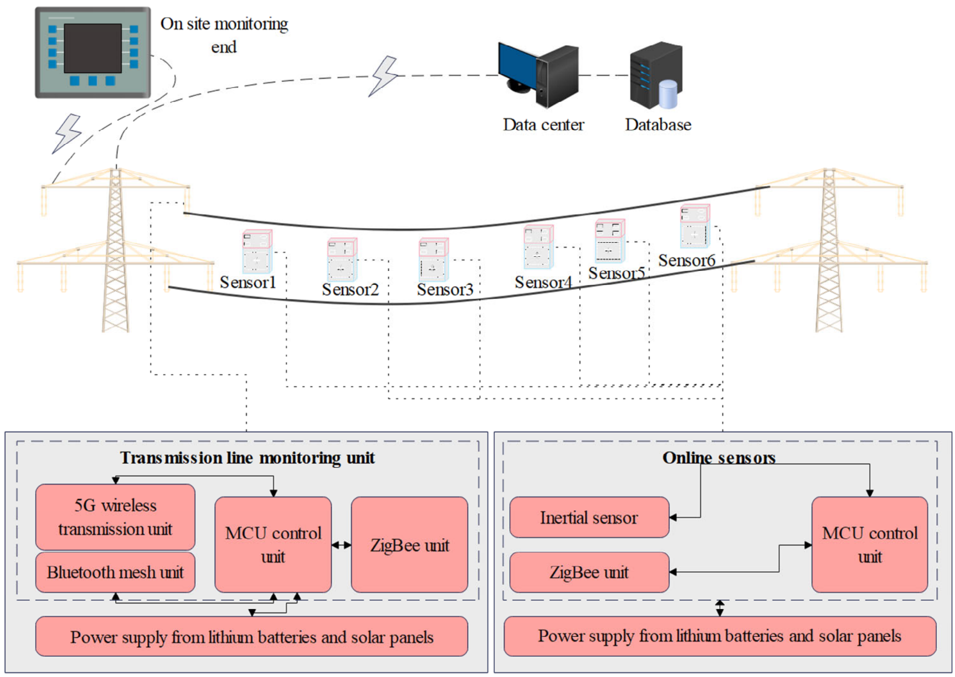
Each row in the matrix has and only has a number of 1, which indicates that this point is the measurement point and the location where the label is placed, corresponding to an element in the original data. In addition, all others are 0, indicating that these points are not measuring points.

3 Construction and test of the system

3.1 Construction of the system

In this paper, the system is used to measure the amplitude and frequency of transmission line galloping, and inertial measurement unit is used as the core sensor of transmission line galloping monitoring, and the overall design of the transmission line galloping monitoring system as shown in Figure 8 is carried out.

Figure 8 Scheme diagram of the overall design of the system (see online version for colours)



Study the errors and sources of wire dancing reconstruction, as well as their impact on the restoration effect. Bayesian compressed sensing transforms the compressed sensing problem into a prior constrained linear regression problem for solving sparse coefficients, estimating sparse coefficients and noise variance based on measurement matrices and measured signals. In the process of solving sparse coefficients, the correlation vector machine method is used to assume prior and estimate parameters, and a hierarchical prior model is used to promote sparsity. After a geological disaster occurs, the system will detect abnormal wire conditions and process the collected information, which will be transmitted to the system terminal interface to remind the staff.

After the design of the whole system, it includes galloping line sensor, galloping monitoring tower terminal, galloping monitoring centre and mobile phone monitoring terminal and other parts. The galloping line sensor is directly fixed on the transmission line, and the original parameters of angular velocity and acceleration of line galloping are collected mainly by six-axis inertial sensor.

The main task of online sensors is to sensitive and collect the original parameters of line dancing, and wirelessly transmit the data to the monitoring tower terminal. When the online sensor is working, the six axis inertial measurement unit monitors the original parameters of the dancing motion; the microprocessor schedules the work of the entire online sensor, while collecting parameters and wirelessly sending data through ZigBee. Therefore, the six axis inertial sensor determines the accuracy of the collected raw dance data, the microprocessor determines whether the online sensor can collect and send dance data normally, and the ZigBee wireless module determines whether dance data can be stably and accurately transmitted. Therefore, it is necessary to make the correct selection of the above key components.

The zero bias stability parameters of accelerometers and gyroscopes in six axis inertial sensors have a significant impact on the accuracy of integral calculation of motion displacement. For this topic, it directly affects the identification accuracy of dance amplitude. Therefore, when selecting devices, in addition to fully considering factors such as whether the devices meet the environmental conditions and device costs, it is also necessary to consider performance parameters such as zero bias stability of the devices. The determination of the spatial attitude and displacement motion parameters of the line can be obtained by integrating the angular velocity output by the gyroscope in the six axis sensor to obtain the attitude change of the line relative to the navigation coordinate system; The motion acceleration of the circuit can be determined based on the output of the accelerometer, but at this time, the acceleration is in the carrier coordinate system at each motion moment. Therefore, it is necessary to use the calculated spatial attitude to unify the motion acceleration in the solution coordinate system, and obtain its displacement transformation after secondary integration. According to the above workflow, the errors output by accelerometers and gyroscopes will be introduced into the motion acceleration in the navigation coordinate system, affecting the final solution accuracy.

Based on the environmental conditions used by the inertial sensor and the requirements for zero bias stability determined in the selection criteria, the six axis inertial sensor (IMU) model ADIS 16470 from analogue devices was ultimately selected.

The microcontroller (MCU) of the online sensor mainly collects the output data of the six axis sensor and transmits it to the monitoring tower terminal through ZigBee. The work complexity of the main control chip is relatively low, so there are no special requirements for the performance of the control chip. However, considering the difficulty of online power supply, its power consumption should be as low as possible, and the interface resources of the chip can meet the project requirements.

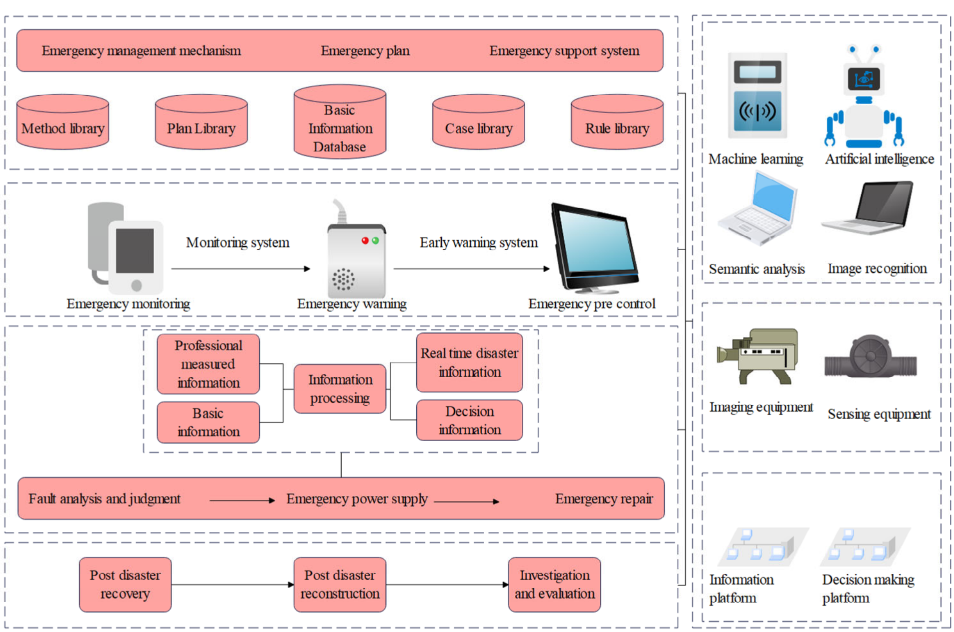
If multiple online sensors are installed on the transmission line, they need to be networked with the monitoring tower terminals to send raw dance data, while also requiring low power consumption, low cost, and high reliability of wireless transmission. These requirements are exactly the characteristics of ZigBee communication. Therefore, ZigBee wireless communication technology is chosen for wireless communication between it and the tower terminals.

The terminal on the dance monitoring tower is a crucial component of the entire dance monitoring system. It is responsible for receiving the original dance parameters of online sensors, and then identifying the dance amplitude, frequency and other characteristic parameters through algorithms. Finally, the calculated dance characteristic parameters are wirelessly transmitted to the monitoring end. Due to the relatively easy power supply of the tower system compared to the online system, more functions are completed at the tower terminal. So the key component selection for the tower terminal mainly includes the selection of microprocessors (MCUs), 4G communication modules, and Bluetooth mesh communication modules. The ZigBee module model is the same as the online sensor, but the working mode is different.

Data pre-processing: based on the characteristics and usage experience of inertial sensors, there are errors such as random zero drift and scale factor deviation in the device. At the same time, the device is easily affected by errors such as random noise and pulse signals. Therefore, the original output data of the sensor needs to be pre-processed to improve data accuracy. Dancing posture calculation: Dancing spatial posture is a key intermediate parameter in the identification process of line dancing characteristic parameters, providing coordinate transformation relationships for the motion acceleration coordinate system and gravity acceleration removal. Accurate dancing posture calculation is an important foundation for accurate identification of dancing characteristic parameters. Dance characteristic parameter identification: Based on the processed acceleration data, the displacement of the motion, i.e., the amplitude of the line dance, is obtained through an integration algorithm. The frequency of the dance can be further identified based on the temporal variation of the amplitude.

The emergency management of geological disaster damage of transmission lines can be divided into four stages: emergency preparedness, emergency prevention, emergency response and recovery and reconstruction, as shown in Figure 9. Digital empowerment is the whole process of empowering digital technology to the decision-making of geological disaster emergency management in urban distribution network. Through digital technology and platform, it fully exploits the knowledge and laws behind data, realises the intelligence and automation of emergency decision-making, and ensures the accuracy of emergency management and the timeliness of emergency disposal. In the stage of geological disaster emergency preparedness of urban distribution network, basic information databases such as pre-plan database, rule database, case database and method database are constructed through digital technology to provide data support for geological disaster emergency management of urban distribution network. Moreover, digital technology can improve the emergency management mechanism, and clarify the management mode, internal relationship and responsibilities of all participants in the geological disaster emergency management of urban distribution network. In addition, the management of emergency plans is carried out through digital technology, which provides action guidelines for the emergency management of geological disasters in urban distribution networks.

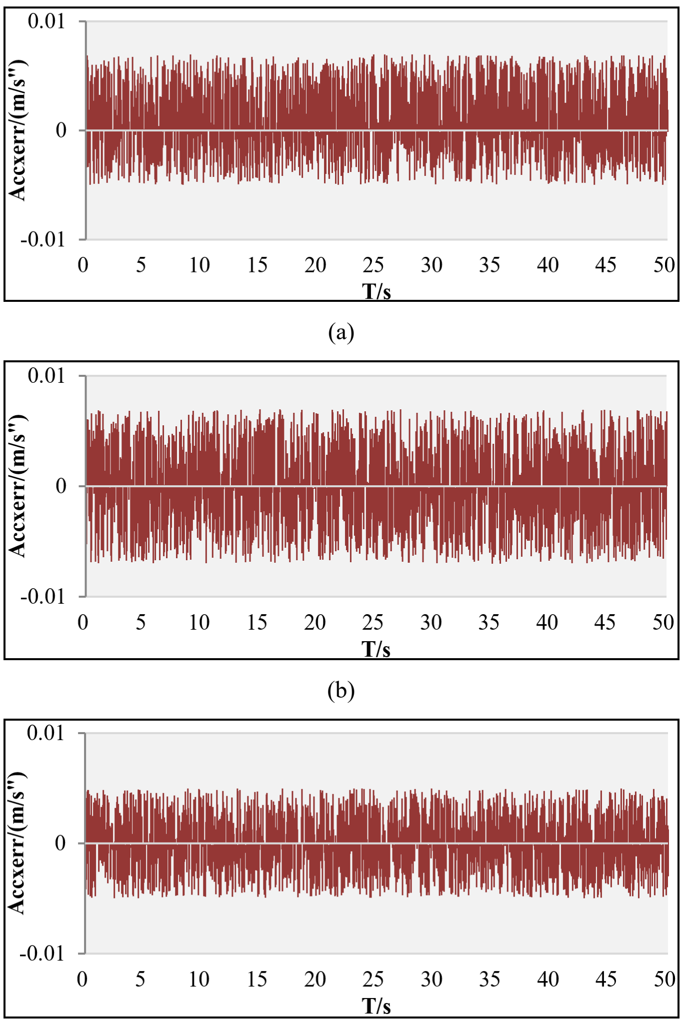
Figure 9 Decision-making framework of the emergency management of geological disaster damage of urban transmission network (see online version for colours)



3.2 Test of the system

Under the static condition, the bias stability of accelerometer is assumed to be 300 μg, and the bias stability of gyroscope is assumed to be 10 °/h. According to the above theory, the simulation output acceleration and angular velocity error curves are shown in Figures 10 and 11, and the simulation curves of the x, y and z-axis motion displacement errors obtained by integrating the sensitive motion acceleration of this inertial sensing combination are shown in Figure 12.

Figure 10 Acceleration error simulation curve, (a) x-axis simulation acceleration error curve (b) y-axis simulation acceleration error curve (c) z-axis simulation acceleration error curve (see online version for colours)



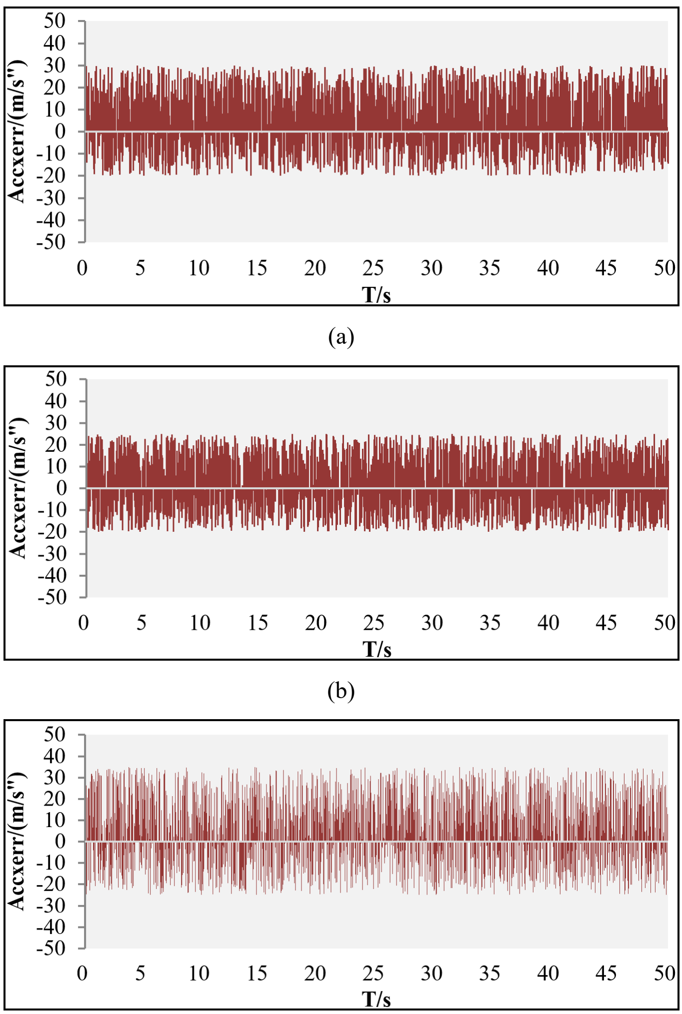
(a)

(b)

(c)

From the analysis of figure, it can be seen that the acceleration and angular velocity errors caused by geological disasters detected by the intelligent online monitoring technology model proposed in this paper are within a reasonable range. Therefore, the model proposed in this paper can effectively detect geological disaster damage of transmission lines when encountering geological disasters, and carry out early warning and reminding through the intelligent system proposed in this paper. After that, this paper validates the decision-making effect of the emergency management decision-making system of geological disaster of urban transmission network proposed in this paper. Moreover, this paper evaluates the strategy effect by expert evaluation method and percent evaluation method, and verifies it by multiple groups of decisions, and obtains the experimental results shown in Table 1.

Figure 11 Simulation curve of angular velocity error, (a) x-axis simulation angular velocity error curve (b) y-axis simulation angular velocity error curve (c) z-axis simulation angular velocity error curve (see online version for colours)



(a)

(b)

(c)

From the evaluation results in Table 1, it can be seen that the early warning and decision-making model of geological disaster damage of transmission lines based on intelligent online monitoring technology proposed in this paper can make reliable decision-making suggestions after geological disasters occur, and the evaluation is distributed between [80, 89], so it can play a certain role in the early warning and decision-making of geological disaster damage of subsequent transmission lines.

To further verify the advantages of the proposed online warning decision-making model for transmission lines compared to existing research, this paper was compared with the transmission line warning decision-making models proposed in Nirmal (2020) and Coletta et al. (2020). A simulation platform was used to construct the system, and expert evaluation was used as a quantitative evaluation method. The experimental results are shown in Table 2.

From the above research, it can be seen that the method proposed in this article performs well in the early warning and decision-making of transmission line monitoring compared to existing models, and has certain advantages compared to existing research.

Several natural geological disasters were simulated using MATLAB, and a total of 10 sets of experiments were conducted to evaluate the accuracy of the model's early warning under geological disasters. The experimental results are shown in Table 3.

From Table 3, it can be seen that the model proposed in this article plays an important role in geological disaster warning for transmission lines, facilitating effective response strategies in advance and effectively reducing the impact of geological disasters on transmission lines.

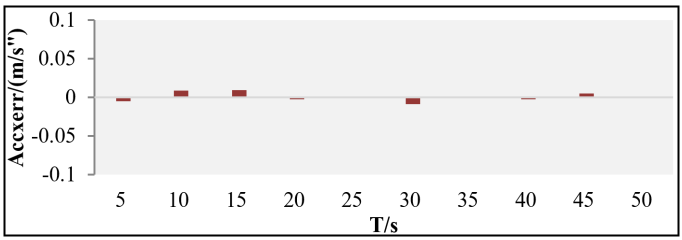
Table 1 Evaluation of decision-making effect of the early warning system of geological disaster damage of transmission lines

Num	*Effects on decision-making*
1	87.49
2	82.24
3	80.93
4	83.44
5	83.86
6	82.12
7	87.92
8	87.99
9	88.97
10	87.22
11	87.42
12	85.53
13	88.83
14	82.50
15	87.32
16	82.37
17	83.22
18	85.13

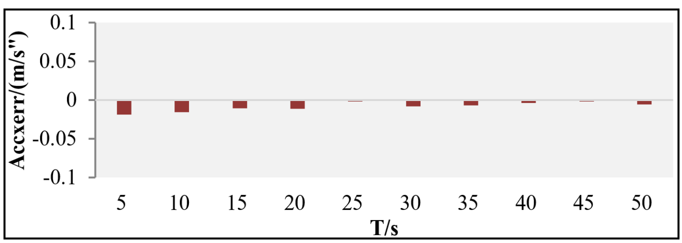
Table 2 Model comparison results

	Warning effect	*Decision effectiveness*
The model of this article	85.32	82.35
The model of Nirmal (2020)	79.25	77.24
The model of Coletta et al. (2020)	77.32	74.29

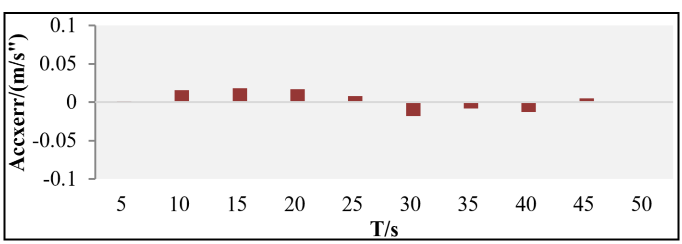
Figure 12 Simulation curves of displacement errors of x, y, z-axis, (a) x-axis simulation displacement error curve (b) y-axis simulation displacement error curve (c) z-axis simulation displacement error curve (see online version for colours)



(a)



(b)



(c)

Research has gradually evolved from post disaster assessment to pre disaster monitoring and early warning. Among them, monitoring and early warning methods have been widely applied in fields such as hydropower engineering, bridge engineering, road engineering, landslides, and have achieved good results. However, there are relatively few monitoring and early warning systems developed for transmission line towers. The adverse climate characteristics have raised higher requirements for the transmission of energy supply data and logistics maintenance of monitoring and early warning systems, and the damage mode of power transmission towers is different from general road engineering or landslide engineering. Therefore, conventional engineering monitoring and early warning systems cannot be directly used for monitoring and early warning of power transmission towers in permafrost areas. It is necessary to develop monitoring and early warning systems that are suitable for the damage characteristics and working environment of power transmission towers. Through online dictionary learning, a sparse dictionary that matches the wire dancing is constructed, and combined with Bayesian algorithm, high-precision reconstruction of the wire is performed at low sampling rates to achieve real-time monitoring of wire dancing, thereby achieving real-time monitoring of transmission lines in geological hazard environments.

Table 3 Model's early warning effect on geological hazards

Number	*Warning effect*
1	93.84
2	90.24
3	88.61
4	88.67
5	93.38
6	91.46
7	88.91
8	90.12
9	92.99
10	88.16

4 Conclusions

At present, the early warning system for transmission lines damaged by geological disasters has realised the functions of detecting, identifying and tracking moving targets and early warning based on transmission line state information such as angle and time at the software algorithm level. Moreover, different researchers choose different algorithms to realise the above functions. However, the return period prediction can only get the probability of geological disasters, but cannot predict the geological thickness of transmission lines in a short time, and cannot provide specific guidance for ice melting and deicing work of power departments in the period prone to geological disasters. Treating transmission lines as a curve in three-dimensional space, under the premise of compressive sensing theory, analysing the sparsity of dancing wires, and reconstructing dancing wires using three-dimensional coordinate information of certain points on the wires. Replacing traditional fixed sparse bases with a super complete dictionary containing prior dance information combined with real-time measurement information, enhances the sparsity of dance wires. The emergency management of geological disaster damage of transmission lines can be divided into four stages: emergency preparedness, emergency prevention, emergency response and recovery and reconstruction. In addition, from the decision evaluation results, we can see that the early warning decision-making model of geological disaster damage of transmission lines based on intelligent on-line monitoring technology proposed in this paper can make reliable decision-making suggestions after geological disasters occur.

Due to the limited sample data on wire dancing in real life, this paper adopts simulation to obtain samples. The sample has been trained to be as close as possible to real dance data, but during the dictionary training process, the simulated sample data still contains far less information than all dance situations. Therefore, the subsequent work is to collect a large amount of existing monitoring data in reality, further improve the training effect of the model in this paper, and further enhance the reliability of transmission line monitoring.

This article constructs an online monitoring system for wire dancing using the absolute three-dimensional coordinate information obtained by ultra wideband positioning technology and the theoretical framework of compressed sensing. However, due to limited laboratory conditions, there is still a slight gap between the dancing experiment of transmission lines and the dancing of wires in real situations. Although both simulation and experiments have proven the effectiveness and feasibility of this method, there are still many aspects of the system that need to be improved and strengthened. The causes of transmission line dancing are relatively complex. In this paper, the design and reconstruction process of the dancing dictionary did not consider the mechanical information of transmission lines. The next step is to combine the two.

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