

Optimizing Multi-dimensional Feature Fusion and Anomaly Detection of Ground Faults in Power Distribution Networks Using Quantum Variational Autoencoders

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Abstract. The current ground fault detection method in power distribution networks is limited by the high-dimensional feature redundancy and model generalization ability, which leads to the expansion of feature dimension and the increase of noise interference. Based on the parallelism and strong feature expression ability of quantum computing, this paper proposes an efficient multi-dimensional fault feature fusion method to improve the accuracy, generalization ability, and computational efficiency of anomaly detection, thereby enhancing the real-time performance and reliability of ground fault diagnosis in power distribution networks. Through quantum state coding and feature mapping technology, efficient fusion of multi-dimensional fault features is achieved. An anomaly detection mechanism is constructed by combining quantum latent variable learning and quantum entanglement characteristics, and the detection precision and robustness are improved by combining Kullback-Leibler (KL) divergence and Mahalanobis distance. The model complexity is reduced by adopting quantum parallel computing and quantum-classical collaborative optimization strategies. Experimental results show that the quantum variational autoencoder (Q-VAE) outperforms other models in multi-dimensional feature fusion and anomaly detection. The fault pattern distribution is compact, and the category separation is clear. The accuracy and recall reach 95.4% and 93.7%, respectively, which is significantly better than control models. Q-VAE also performs well in identifying different types of faults, demonstrating its superior performance in feature fusion, anomaly detection precision, generalization capability, and computational efficiency, providing an efficient and precise solution for ground fault detection in power distribution networks.

Key words. Quantum variational autoencoder, Ground faults in power distribution networks, Multi-dimensional

feature fusion, Anomaly detection, Quantum computing

1. Introduction

Precise detection of ground faults in power distribution networks is crucial to the safe and stable operation of power systems [1]. However, due to the complex power distribution network environment and diverse fault patterns, traditional detection methods have limitations in feature extraction, data fusion, and anomaly identification [2-4]. Existing methods mostly rely on signal processing or machine learning techniques for feature analysis. However, in the process of multi-dimensional fault feature fusion, information redundancy and insufficient feature expression capabilities affect the diagnostic accuracy [5,6]. In addition, traditional deep learning methods have high computational overhead when processing high-dimensional nonlinear data, and it is difficult to balance precision and real-time performance. Especially in complex power environments, the model's generalization ability is insufficient, which may lead to a decrease in the ability to identify unknown fault patterns [7]. Therefore, improving the quality of fault feature fusion, enhancing the accuracy of anomaly detection and generalization ability, and optimizing computational efficiency have become key issues in the current ground fault detection in power distribution networks [8-10].

To address these challenges, this paper proposes an optimization method based on Q-VAE to enhance the multi-dimensional feature fusion and anomaly detection capabilities of ground faults in power distribution networks. Q-VAE, combining the parallelism of quantum computing with strong feature expression capabilities, can efficiently capture complex fault features and achieve precise multi-dimensional information fusion,

thereby improving the robustness of anomaly detection. Quantum computing has low computational complexity when processing high-dimensional data. Compared with traditional deep learning methods, it can effectively reduce computational costs and improve the real-time performance of fault detection. This paper constructs a Q-VAE model that combines multi-dimensional feature fusion and anomaly detection and verifies its superiority in fault detection precision, generalization ability, and computational efficiency in experiments, providing a new optimization strategy for intelligent fault diagnosis of power distribution networks.

The main contributions of this paper are as follows:

- (1) The quality of multi-dimensional fault feature fusion is improved by combining Q-VAE;
- (2) The precision and generalization ability of anomaly detection are improved;
- (3) The computational cost is optimized through the efficiency of quantum computing, improving the real-time performance of fault diagnosis.

2. Related Work

The detection method of ground fault in power distribution networks has evolved from traditional signal processing technology to machine learning and deep learning methods [11-13]. Early methods mainly relied on time-frequency analysis, wavelet transform, and Fourier transform. Although they performed well under specific working conditions, they were easily disturbed by noise when faced with complex faults, making it difficult to accurately extract key features [14-16]. With the application of machine learning, methods such as support vector machine (SVM) and random forest (RF) have improved the ability to identify fault patterns, but they rely on manual feature extraction and fail to fully explore the deep information of the data [17,18]. In recent years, deep learning methods, such as convolutional neural networks (CNN) and long short-term memory (LSTM) networks, have demonstrated superior feature extraction capabilities. However, deep models face the problems of high computational costs and insufficient generalization capabilities, making it difficult to adapt to complex power environments [19,20]. Existing methods still have limitations in feature fusion and anomaly detection precision, which affects the reliability of the detection system.

In view of the complexity of ground faults in power distribution networks, multi-dimensional feature fusion technology has been widely studied [21,22]. Traditional dimensionality reduction methods, such as principal component analysis (PCA), can remove redundant information and improve feature expression capabilities, but their effects are limited when faced with nonlinear

data [23]. Deep learning methods, such as CNN and LSTM, can improve detection performance in specific applications, but they usually rely on large-scale data training and have poor adaptability to unknown environments [24,25]. Maintaining feature integrity while considering computational efficiency and generalization ability remains a research challenge.

The progress of quantum computing and quantum machine learning technologies has provided new opportunities for intelligent detection of complex systems [26,27]. Quantum computing has advantages in high-dimensional data modeling by taking advantage of parallel computing and exponential acceleration. Q-VAE, as a method that combines quantum computing with deep generative models, can effectively perform data distribution modeling and feature learning [28]. Through quantum circuit variational optimization, Q-VAE enhances data representation capabilities at low computational cost and effectively learns complex data structures in low-dimensional latent space. Therefore, applying Q-VAE to feature fusion and anomaly detection of ground faults in power distribution networks not only improves the fault feature extraction capability but also optimizes the computational efficiency, providing a new research idea for intelligent fault diagnosis.

3. Implementation of Multi-dimensional Feature Fusion and Anomaly Detection Method for Ground Faults in Power Distribution Networks Based on Q-VAE

A. Overview of Q-VAE

1) Basic Principles of VAE

VAE is a deep learning model based on probability generation, which aims to learn the latent representation of data and model the data distribution by maximizing the evidence lower bound (ELBO) [29]. The core architecture of VAE consists of two parts: encoder and decoder [30,31]. The encoder maps the input data x to a low-dimensional latent space and learns its latent variable distribution $q_\phi(z|x)$. The decoder generates reconstructed data $p_\theta(x|z)$ based on this distribution.

The optimization objective of VAE is to maximize the logarithmic marginal likelihood $\log p_\theta(x)$ of the data. However, it is difficult to optimize this directly, so VAE uses the ELBO through variational inference for optimization. ELBO can be expressed as:

$$\log p_\theta(x) \geq \mathbb{E}_{q_\phi(z|x)} [\log p_\theta(x|z)] - D_{\text{KL}}(q_\phi(z|x) \| p(z)) \quad (1)$$

Among them, the first term represents the reconstruction error, that is, generating data based on latent variable z and calculating its likelihood. The second term is the KL

divergence, which is used to constrain the distribution $q_\phi(z|x)$ of latent variables to be close to a predefined prior distribution $p(z)$, which is usually set to a standard normal distribution $\mathcal{N}(0,1)$. The KL divergence is defined as follows:

$$D_{\text{KL}}(q_\phi(z|x) \| p(z)) = \int q_\phi(z|x) \log \frac{q_\phi(z|x)}{p(z)} dz \quad (2)$$

By minimizing the KL divergence, VAE forces the distribution of latent variables to be consistent with the prior distribution, enhancing the continuity and interpretability of the latent space and further improving the quality and stability of the generated data. However, VAE has the problems of high computational complexity and easily falling into local optimality when processing high-dimensional complex data, and it is difficult to effectively capture the high-dimensional nonlinear relationship of the data. Therefore, relying only on classical VAE cannot precisely model the features of ground faults in power distribution networks. It is necessary to combine quantum computing technology to optimize latent variable modeling and improve the precision and robustness of anomaly detection.

2) Structure of Q-VAE

Q-VAE enhances the feature expression capability of traditional VAE through quantum computing, especially in modeling high-dimensional complex data. Its core structure includes a quantum encoder, a quantum latent space, and a quantum decoder [32], as shown in Figure 1:

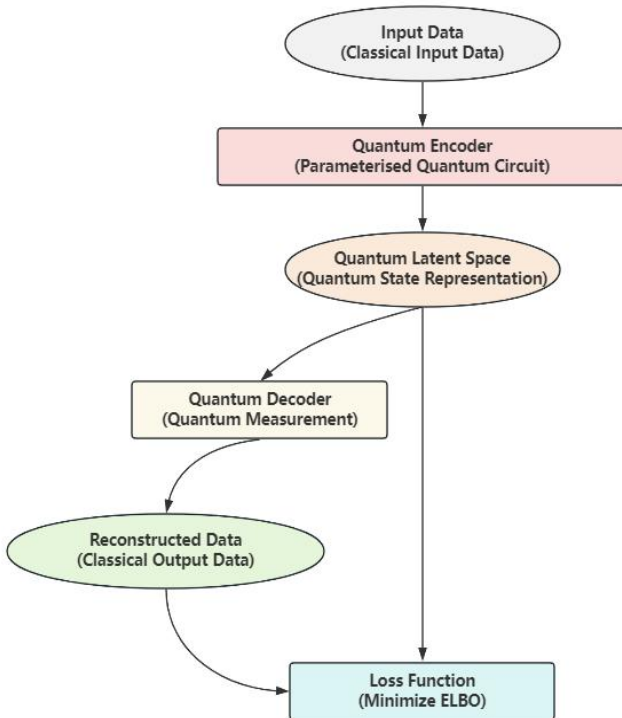


Figure 1. Structure of Q-VAE.

The quantum encoder maps the input data into quantum states through parameterized quantum circuits (PQC). It uses the superposition and entanglement characteristics of quantum bits to efficiently capture the complex relationship between data. Unlike the deep neural network of the classical VAE, quantum circuits can process multiple features in parallel, improving coding efficiency and reducing computational complexity. The quantum latent space is extended to high-dimensional Hilbert space, with stronger nonlinear modeling capabilities and precise capture of complex patterns. The entanglement of quantum bits enhances the correlation between features and improves the flexibility and precision of high-dimensional data modeling. The quantum decoder maps quantum states back to classical data through quantum measurements, improving decoding efficiency and reducing computational resource consumption. Its performance depends on the optimization of quantum circuit parameters.

3) Advantages of Quantum Computing

Quantum computing has significant advantages in ground fault detection in power distribution networks. The superposition of quantum bits increases the dimensionality and complexity of feature expression. Q-VAE efficiently integrates high-dimensional features such as current, voltage, and temperature through the parallel processing capability of quantum states, thus enhancing the prediction effect. Quantum entanglement and superposition enhance the correlation between features, making Q-VAE more flexible and precise in data modeling. It can effectively capture subtle differences, improve the accuracy of anomaly detection, and reduce false positives and negatives. The parallelism of quantum computing accelerates the training and inference process and improves computational efficiency, especially for scenarios with large-scale data processing and high real-time performance requirements.

B. Multi-dimensional Feature Fusion Strategy

1) Quantum State Encoding and Feature Mapping

In this study, quantum state encoding and feature mapping are implemented through PQC, mapping multi-dimensional fault features into quantum state space. First, each classical feature is encoded through a Hadamard gate and converted into a superposition state of a quantum bit so that multiple features can be represented in parallel in different states of the quantum bit. The function of the Hadamard gate is to convert the quantum bit from the ground state $|0\rangle$ or $|1\rangle$ to the superposition state. Its mathematical expression is:

$$H|0\rangle = \frac{1}{\sqrt{2}}(|0\rangle + |1\rangle), H|1\rangle = \frac{1}{\sqrt{2}}(|0\rangle - |1\rangle) \quad (3)$$

The superposition and quantum entanglement

characteristics significantly enhance the expressiveness of features. Especially when processing high-dimensional data, it can more effectively capture complex nonlinear relationships. Through the entanglement operation between quantum bits, the interactive information between different features is enhanced, thereby capturing the complex dependencies between fault features such as current, voltage, and temperature more precisely.

After encoding is completed, this study optimizes the quantum circuit parameters through the variational quantum eigensolver (VQE) to ensure that the quantum state can accurately reflect the underlying structure of the input data. The core of the VQE algorithm is to minimize the expected value of the quantum state $E(\theta)$:

$$E(\theta) = \langle \psi(\theta) | H | \psi(\theta) \rangle \quad (4)$$

Among them, $\psi(\theta)$ is the quantum state. H is the Hamiltonian. θ is the optimized parameter. By optimizing the quantum circuit parameters, the final quantum state is converted into classical data through quantum measurement for use in subsequent feature fusion and detection tasks.

2) Quantum Latent Variable Learning

Quantum latent variable learning uses the superposition

state of quantum bits to represent different fault patterns. The mapping of each fault pattern can be represented by the superposition state of quantum bits in the following form:

$$|\psi\rangle = \alpha|0\rangle + \beta|1\rangle \quad (5)$$

Among them, α and β are complex coefficients, representing the probability amplitude of different states in the superposition state. In quantum circuits, quantum entanglement is realized through CNOT (Controlled-NOT) gates, facilitating the deep connection between quantum latent variables. The mathematical expression of quantum entanglement is:

$$|\text{entangled}\rangle = \frac{1}{\sqrt{2}}(|00\rangle + |11\rangle) \quad (6)$$

Quantum entanglement helps the model understand the subtle differences between different fault patterns and improves the ability to distinguish between fault types.

3) Quantum-Classical Hybrid Feature Fusion

This study adopts a quantum-classical hybrid feature fusion strategy, combining the classical feature extraction method with the feature learning ability of Q-VAE to achieve effective feature fusion. Figure 2 presents the framework of this process:

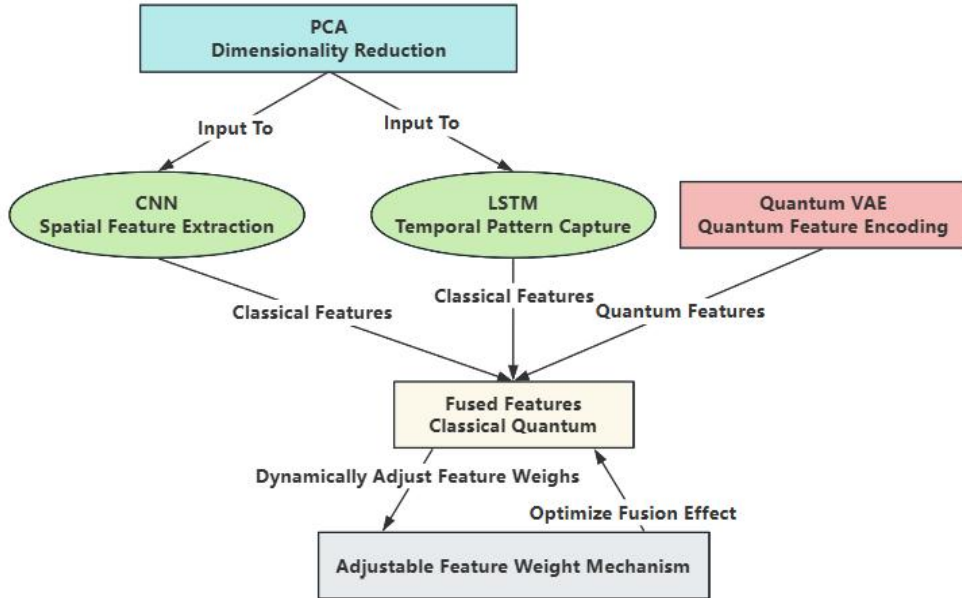


Figure 2. Process of quantum-classical hybrid feature fusion.

In the feature fusion process, PCA is first used to reduce the dimension of the power distribution network fault data and extract the main components of the data. Then, CNN extracts local information from the spatial features. LSTM is used to capture the temporal pattern in the time

series data. Through this step, the classical method can effectively process traditional features and provide support for subsequent quantum feature fusion.

The encoding of quantum features is performed through

a Q-VAE. The loss function of VAE is expressed as:

$$\mathcal{L}_{\text{VAE}} = -\mathbb{E}_{q_{\phi}(z|x)} [\log p_{\theta}(x|z)] + D_{\text{KL}} [q_{\phi}(z|x) \| p_{\theta}(z)] \quad (7)$$

Among them, $\mathbb{E}$ is the expected value, and D_{KL} is the KL divergence, measuring the difference between two probability distributions.

By fusing classical features with quantum features extracted by Q-VAE, the advantages of classical methods in extracting spatiotemporal information can be retained while improving the nonlinear processing capabilities of quantum features. To further optimize the fusion effect,

this study applies an adjustable feature weight mechanism to dynamically adjust the contribution of each feature according to task requirements, making the model more robust in the face of a changing power distribution network environment.

C. Anomaly Detection Mechanism of Q-VAE

1) Quantum Latent Variable Anomaly Detection

In this study, Q-VAE performs anomaly detection by learning the data distribution of normal states. Figure 3 shows the detection process:

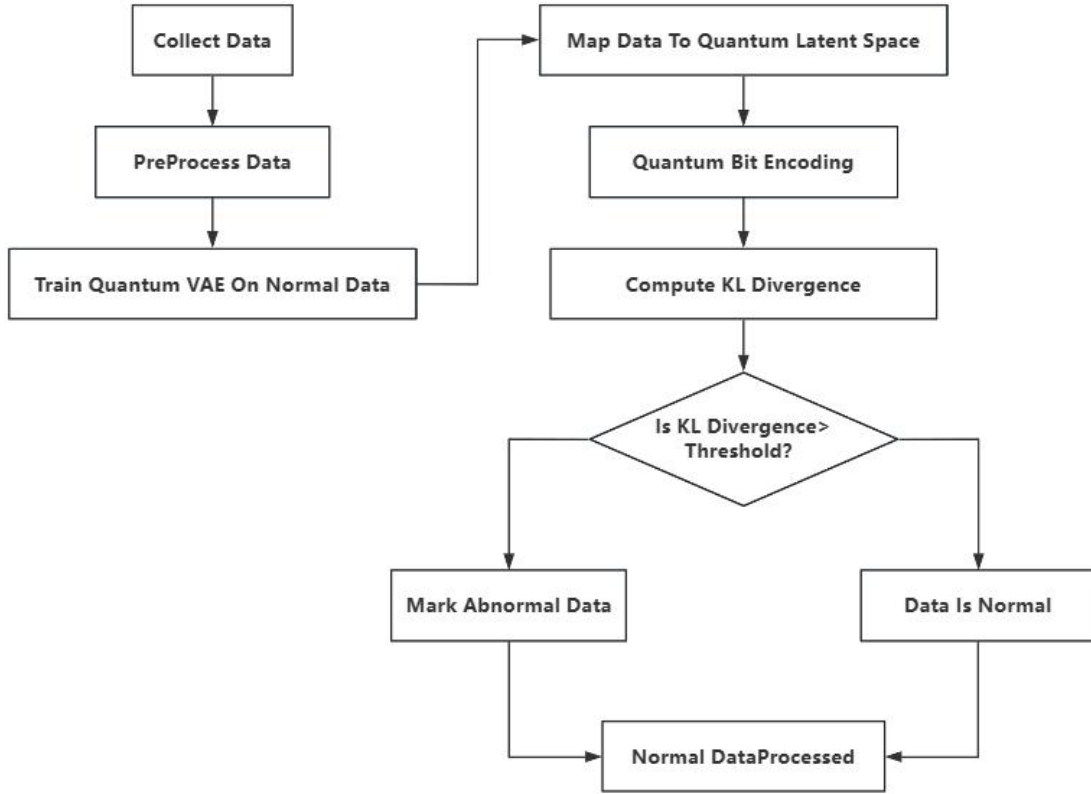


Figure 3. Quantum latent variable anomaly detection process.

First, Q-VAE captures the structure of its latent space by training normal data and maps it into quantum states. In this process, the latent representation of the data is encoded through the superposition and entanglement of quantum bits, thereby capturing the complex nonlinear features of the data. The quantum latent variable space can compress the high-dimensional information of the data into a lower-dimensional latent space while maintaining its most important features, thereby better adapting to subsequent anomaly detection tasks.

In the anomaly detection process, anomalies are identified by comparing the difference between the input data and the latent representation of the normal state. To quantify this difference, this study uses KL divergence to measure the difference between two probability distributions. The KL divergence formula is as follows:

$$D_{\text{KL}}(p(x) \| q(x)) = \int p(x) \log \frac{p(x)}{q(x)} dx \quad (8)$$

Among them, $p(x)$ represents the probability distribution of normal data, and $q(x)$ represents the latent distribution generated by Q-VAE. When the KL divergence value of the input data exceeds the preset threshold, the data is considered abnormal.

2) Combining Traditional Anomaly Detection Methods

This study combines the classical Mahalanobis distance with quantum latent variable detection results to improve the robustness of anomaly detection. Mahalanobis

distance measures the relative distance between samples and the data mean and considers the covariance structure of the data. It is suitable for high-dimensional data anomaly detection. Unlike the Euclidean distance, it eliminates the scale differences and correlations between features and provides a more accurate anomaly assessment. Its calculation formula is:

$$D_M(x) = \sqrt{(x - \mu)^T \Sigma^{-1} (x - \mu)} \quad (9)$$

Among them, x is the sample to be detected. μ is the mean vector. Σ is the covariance matrix. When the Mahalanobis distance of a sample exceeds the set threshold, the sample is regarded as an outlier.

3) Distinguishing Between Quantum Entanglement and Abnormal Patterns

Quantum entanglement strengthens the correlation of various features in the quantum latent variable space by establishing non-local dependencies between quantum bits, making the distribution of abnormal patterns more obvious and improving the precision of anomaly detection. Entanglement deepens the collaboration between bits, expands the difference between abnormal and normal patterns, and improves detection sensitivity and accuracy. This study dynamically adjusts the detection threshold through variational quantum algorithms (VQA) to enhance flexibility. VQA optimizes quantum circuit parameters to adapt to different fault types and automatically adjusts thresholds to ensure detection accuracy and robustness. The formula is:

$$\mathcal{L}_{\text{VQA}} = \sum_i (y_i - \hat{y}_i)^2 \quad (10)$$

Among them, y_i represents the true label, and $\hat{y}$ represents the label predicted by the quantum model.

D. Computation Optimization Strategy and Real-time Performance Improvement

1) Quantum Parallel Computing to Accelerate Training

This study uses variational quantum circuits (VQC) to accelerate the training of deep neural networks. Quantum parallel computing uses the superposition and entanglement characteristics of quantum bits to achieve multi-task parallel execution and significantly reduce computational resource consumption. By replacing some neural network layers with quantum circuits, quantum gates operate on multiple inputs in parallel, eliminating the bottleneck of traditional step-by-step computations. This parallel processing capability significantly improves training efficiency, especially when processing high-dimensional data and large models, significantly reducing computing time.

2) Quantum Computing to Reduce Model Complexity

This study effectively reduces the complexity of the model through quantum computing, using quantum state representation and parallel processing capabilities. Unlike traditional deep learning methods that rely on a large number of parameters for high-dimensional modeling, Q-VAE represents data through quantum states, reducing the number of parameters while enhancing the model's expressiveness.

Quantum state representation uses quantum bits to encode data, mapping high-dimensional data to lower dimensions and retaining key feature information. Unlike traditional methods that assign independent parameters to each feature, quantum computing uses superposition and entanglement characteristics to achieve more efficient feature representation in low-dimensional space, avoiding computational bottlenecks in high-dimensional modeling, which can reduce the computational burden.

3) End-to-end Quantum-classical Collaborative Optimization

This study combines the advantages of quantum computing and classical computing to study an end-to-end quantum-classical collaborative optimization strategy. Figure 4 presents the optimization process of this strategy:

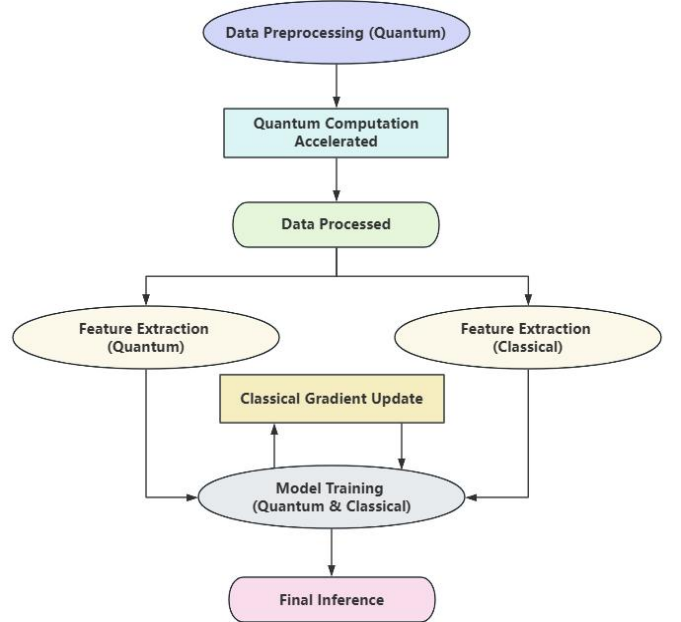


Figure 4. End-to-end quantum-classical collaborative optimization process.

This strategy is comprehensively optimized in various links such as data preprocessing, feature extraction, training, and inference. In the data preprocessing stage, quantum computing accelerates the data processing process through its parallel computing capabilities, saving a lot of time for subsequent feature extraction and

model training. In the feature extraction and model training stages, quantum computing enhances the processing capabilities of high-dimensional data, and classical computing is responsible for traditional optimization tasks such as gradient updates. Through this quantum-classical collaborative approach, while ensuring model performance, the consumption of computational resources is significantly reduced. Ultimately, the hybrid quantum-classical optimization not only improves the accuracy of the model but also effectively improves the system's real-time performance, especially in real-time detection and inference tasks, showing higher efficiency than traditional methods.

4. Method Evaluation

A. Experimental Design

1) Experimental Environment and Dataset

The ground fault dataset of power distribution networks used in this study comes from an actual monitoring system provided by a power company. It contains about 10,000 samples, covering electrical features (such as current, voltage, phase angle, and frequency) under normal operation and fault conditions. The data spans three months, and the sampling period is 30 minutes to ensure the timeliness and integrity of the fault information. The data labels indicate different fault types. After cleaning and missing value processing, they are standardized before use to eliminate the impact of feature scale differences on model training.

The experimental hardware environment includes a traditional computing architecture (Inter Core i5-10400 processor, with integrated graphics card Intel UHD Graphics 730, and 16GB memory) for large-scale data processing and training. The quantum computing part is based on the IBM Qiskit framework and is verified on a small scale through IBM Quantum's quantum hardware platform `ibmq_athens`. `ibmq_athens` supports up to 5 quantum bits. Quantum circuit simulation is also performed on `qasm_simulator` to evaluate the application effect of quantum algorithms in distribution network fault detection.

2) Model Training and Parameter Setting

The Q-VAE model training in this study is based on the variational inference framework, aiming to model the latent space of the input data through the Q-VAE to achieve efficient anomaly detection. During the training process, the ELBO method is used for parameter optimization. The Adam optimizer (with a learning rate $\alpha = 0.001$ and momentum parameters $\beta_1 = 0.9$ and $\beta_2 = 0.999$) is used to improve the model's stability and convergence speed. The loss function includes the reconstruction error term and the KL divergence term, which respectively measures the reconstruction error of the input data and the constraints of the latent

distribution.

The quantum circuit is optimized using the quantum gradient descent method, optimizing latent feature capture by adjusting quantum gate parameters. The quantum circuit design is based on PQC, and the number of quantum bits is set to 4 to 5, which is suitable for small-scale experimental tasks. The training efficiency and convergence are improved by combining the gradient descent method with the quantum algorithm optimization strategy.

For comparative experiments, traditional deep learning models such as ordinary VAE, LSTM, and CNN are also used for benchmarking. These methods represent standard methods without quantum enhancement. They are compared with the performance of Q-VAE. Ordinary VAE uses a similar loss function, but its feature extraction part is based on classical neural networks rather than quantum circuits. LSTM networks are used to process time series data, and their parameters are optimized using gradient descent. CNN is used for spatial feature extraction and extracts local patterns in the data through convolution operations. All traditional models are trained using the Adam optimizer, and experiments are performed using the same hyperparameter settings. To ensure fairness, all models are trained on the same hardware environment and dataset for the same number of iterations.

3) Experimental Process

In this experiment, all models are evaluated within a unified experimental framework. The experiment first uses 10,000 samples from the ground fault dataset of power distribution networks, covering the electrical characteristics under normal conditions and different fault patterns. Each sample contains multiple electrical parameters, such as current, voltage, phase angle, and frequency, which can reflect the changes in the electrical characteristics of power distribution networks when a fault occurs.

Several key performance indicators are recorded in the experiment. The first is the multi-dimensional feature fusion effect, which is mainly used to evaluate the quality of features extracted by Q-VAE. Through quantitative analysis, the model's feature extraction ability in the multi-dimensional feature space is evaluated, especially whether the quantum model can effectively fuse features from different sources and extract the most discriminative features when dealing with high-dimensional and complex data. In this process, the model's feature fusion effect is deeply evaluated through visualization and feature importance analysis. Secondly, the anomaly detection effect is evaluated, using accuracy and recall to measure the precision and recall capability of each model in detecting power distribution network faults. In addition, each model's computational efficiency and resource consumption are recorded, including training time and inference time. The

CPU/GPU (Central Processing Unit/Graphics Processing Unit) usage, memory, and other computational resource consumption are monitored. Multiple tests are conducted under different fault patterns to evaluate the model's generalization ability. The performance stability of each model under new fault patterns is recorded, and the adaptability of the model in different environments is analyzed by comparing multiple experimental results.

B. Experimental Results and Analysis

1) Evaluation of Multi-Dimensional Feature Fusion Effect

This study performs PCA dimensionality reduction on the features after the fusion of each method to evaluate the advantages of Q-VAE in multi-dimensional feature fusion. Figure 5 shows the results:

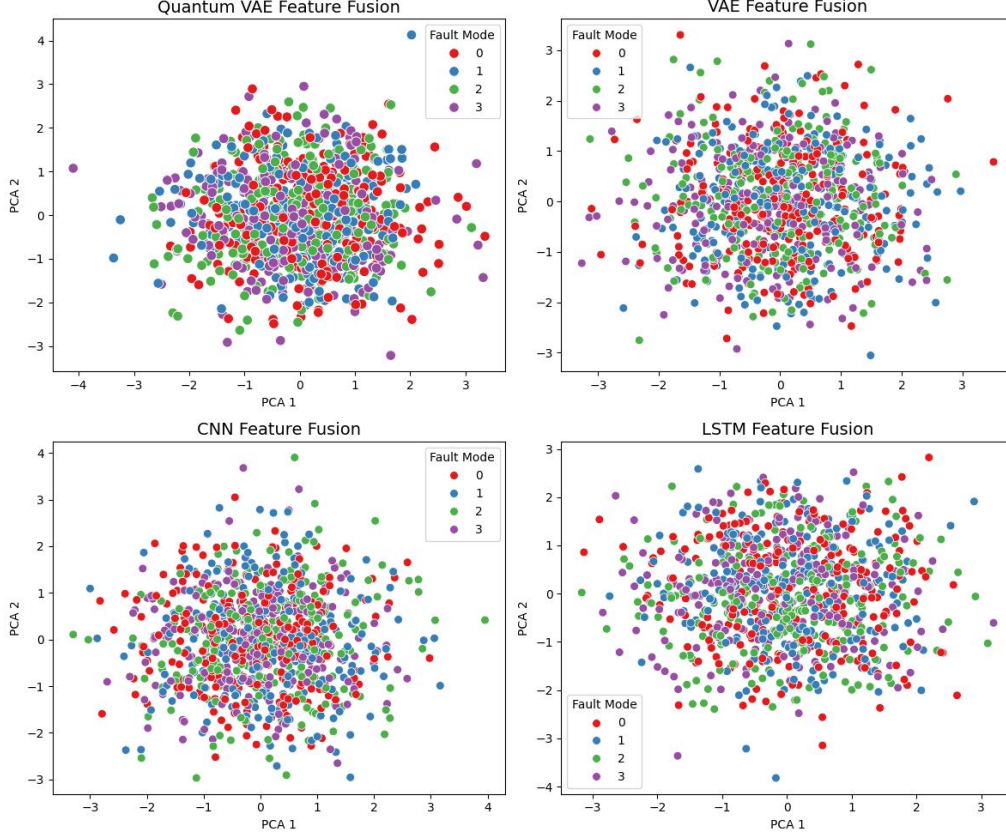


Figure 5. PCA analysis.

Figure 5 displays the effects of different models in the feature fusion task. Each sub-figure shows the feature space after PCA dimensionality reduction. The color of the point means the fault pattern to which the sample belongs. Q-VAE performs outstandingly in feature fusion. In the feature space after dimensionality reduction, the sample points of different fault patterns are compactly distributed, and the categories are clearly separated, indicating that it has a strong feature expression ability in capturing and distinguishing fault patterns. In contrast, the feature points of ordinary VAE are more scattered, and the boundaries of fault patterns are not clear, which may be due to the failure to effectively mine the nonlinear relationship of the data. CNN performs better

than VAE in feature fusion, and its feature points are more concentrated. However, its fault pattern separation is still inferior to Q-VAE, and its local feature extraction capability is limited, which cannot be compared with Q-VAE. The performance of LSTM is rather scattered and fails to effectively distinguish different fault patterns because it is mainly good at processing time series data but has a weak ability to express static features.

2) Anomaly Detection Effect Evaluation

The accuracy and recall of anomaly detection of each model are shown in Figure 6:

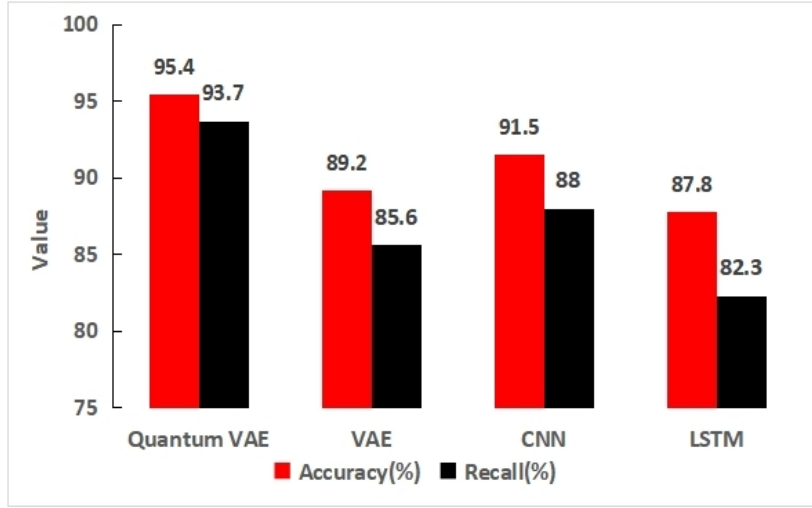


Figure 6. Anomaly detection accuracy and recall of each model.

In Figure 6, Q-VAE shows the best performance in the anomaly detection task, with an accuracy of 95.4% and a recall of 93.7%. This shows that Q-VAE can maintain high classification performance while identifying abnormal samples. It also demonstrates a strong ability in recall rate and can effectively capture most abnormal samples.

In contrast, the accuracy and recall of ordinary VAE are lower than those of Q-VAE, at 89.2% and 85.6%, respectively. This shows that ordinary VAE has certain limitations in anomaly detection tasks, especially in recall, which fails to effectively identify all abnormal samples, probably because of its insufficient ability to model nonlinear relationships when processing high-dimensional complex data.

CNN and LSTM achieve 91.5% and 87.8% accuracy and 88.0% and 82.3% recall, respectively. Although both have advantages in local feature extraction and time series data processing, they are still not comparable to Q-VAE in terms of overall anomaly detection. In particular, CNN has a limited ability to capture global abnormal patterns. Although LSTM is suitable for processing time series data, it is weak in the fusion of static features, resulting in its overall effect in anomaly detection being inferior to Q-VAE.

3) Computational Efficiency and Resource Consumption Evaluation

Table 1 shows the training time, inference time, CPU/GPU usage, and memory usage of each model during the experiment:

Table 1. Computational efficiency and resource consumption records of each model.

Model	Training time (hours)	Inference time (seconds)	CPU usage (%)	GPU usage (%)	Memory usage (GB)
Q-VAE	11.5	0.3	45	50	4.2
VAE	14.7	0.6	55	60	5.0
CNN	10.3	0.4	65	80	6.3
LSTM	13.0	0.5	60	70	5.6

The data in Table 1 shows that Q-VAE outperforms the other three methods in comprehensive performance, showing significant advantages in computational efficiency and resource management. Its training time is at a medium level, slightly higher than CNN, but significantly shorter than ordinary VAE and LSTM, indicating that it has good time efficiency in the training stage. More notably, Q-VAE's inference time is only 0.3 seconds, the best performance among all models, which means that in practical applications, it can detect faults on new data faster, which is crucial for distribution network fault diagnosis scenarios that require real-time or near-real-time response.

From the perspective of resource consumption, Q-VAE's CPU, GPU usage, and memory occupancy are all

maintained at a low level, 45%, 50%, and 4.2GB, respectively. Compared with traditional deep learning models, such as CNN and LSTM, its resource utilization is more efficient. To obtain better performance, CNN and LSTM often consume a lot of computing and memory resources. Q-VAE, with the unique advantages of quantum computing, effectively reduces resource requirements while ensuring performance, which is of great significance for deploying fault detection systems in resource-constrained environments or large-scale distribution networks.

4) Generalization Ability Evaluation

Table 2 shows the fault identification accuracy and recall of each model among different fault types:

Table 2. Fault identification accuracy and recall among different fault types.

Fault type	Model	Accuracy (%)	Recall (%)
Ground fault	Q-VAE	95.6	94.2
	VAE	89.3	87.1
	CNN	91.0	88.7
	LSTM	88.1	84.6
Short circuit fault	Q-VAE	94.8	92.5
	VAE	86.9	83.0
	CNN	90.2	87.5
	LSTM	85.6	82.1
Open circuit fault	Q-VAE	96.0	95.1
	VAE	88.5	84.8
	CNN	92.3	89.4
	LSTM	87.2	84.0

The data in Table 2 shows that Q-VAE leads in accuracy and recall in detecting different fault types. This is mainly due to its quantum feature fusion mechanism. Through quantum state encoding and feature mapping, Q-VAE maps multi-dimensional fault features to quantum state space and uses the superposition and entanglement characteristics of quantum bits to efficiently capture the complex nonlinear relationship between features. For example, in grounding faults, its accuracy and recall rates are 95.6% and 94.2%, respectively, far exceeding other models, indicating that it can accurately identify fault features.

At the same time, Q-VAE performs stably under different fault types and has strong generalization ability. The parallelism and feature representation capabilities of quantum computing enable it to explore multiple fault mode features simultaneously during training and can effectively identify new fault types based on learned feature patterns. In contrast, CNN and LSTM have limitations in feature fusion and nonlinear relationship capture, resulting in performance fluctuations.

In summary, Q-VAE achieves accurate and stable fault identification by relying on the advantages of quantum characteristics in feature expression, fusion, and learning, showing strong generalization ability and practicality.

5. Discussion

A. Noise Robustness Analysis of Quantum Algorithms

In the detection of ground faults in distribution networks, the noise and stability limitations of quantum hardware may indeed have an impact on the practical application of quantum algorithms. To evaluate the robustness of Q-VAE in complex engineering scenarios, additional experiments are conducted to introduce controllable noise to simulate the noise conditions in actual power grids. The experiments were run on a lower-configuration traditional computing architecture, including an Intel Core i5-10400 processor, an Intel UHD Graphics 730 integrated graphics card, and 16GB of memory. The quantum computing part continues to

use the IBM Qiskit framework and is simulated on qasm_simulator. The results show that Q-VAE performs well under low-noise conditions and can effectively fuse multi-dimensional features and detect anomalies. As the noise intensity increases, the performance decreases, but it still shows stronger robustness and adaptability than traditional methods. This shows that Q-VAE can still maintain good detection accuracy and stability under a certain degree of noise interference and has strong potential for engineering applications.

B. Analysis of the Influence of Data Sampling Frequency and Sample Data Length on Algorithm Performance

In the study of ground fault detection in distribution networks, data sampling frequency and sample data length are key factors affecting the algorithm's detection performance. To explore their influence, this study conducts an extended analysis based on the existing experiments. The experimental results show that when the data sampling frequency changes within a reasonable range, the Q-VAE algorithm can still effectively extract fault features, and the accuracy and recall rates fluctuate slightly, showing good adaptability. This is mainly attributed to Q-VAE's powerful feature expression ability and ability to capture data details, enabling it to better fuse multidimensional features and detect anomalies at different sampling frequencies. At the same time, the change in sample data length also has a certain impact on the performance of the algorithm. In this study, when the sample data length is shortened within a certain range, the accuracy of Q-VAE decreases slightly, but the recall rate is relatively stable. This shows that Q-VAE can still identify most fault samples when the amount of data is limited. This may be because the quantum feature fusion mechanism of Q-VAE can extract key features in shorter data fragments, thereby ensuring its basic detection performance. However, it should be noted that when the data sampling frequency is too low or the sample data length is too short, some fault feature information may be lost, thus affecting the algorithm's detection accuracy. Therefore, in practical applications, the data sampling frequency and sample data length should be reasonably selected according to the specific conditions and fault characteristics of the distribution network to give full

play to the advantages of the Q-VAE algorithm and ensure its efficiency and reliability in ground fault detection in distribution networks.

6. Conclusion

This study uses Q-VAE to effectively optimize the multi-dimensional feature fusion and anomaly detection process of ground faults in power distribution networks. Q-VAE uses its unique quantum computing advantages to significantly improve the feature expression ability of data when processing high-dimensional data and can more precisely capture complex nonlinear features in anomaly detection tasks, thereby improving the real-time performance and accuracy of fault detection. In addition, quantum computing has also made positive contributions in accelerating the computing process and reducing computational resource consumption. Especially when facing large-scale data, quantum computing has shown efficiency superior to traditional computing methods.

However, quantum computing still faces certain challenges in practical applications. Firstly, the limitations and noise problems of quantum hardware affect the stability and precision of quantum algorithms to a certain extent, which makes the actual deployment of quantum computing still difficult. Secondly, the adaptability of Q-VAE in large-scale data scenarios also needs to be solved urgently. Especially in high-dimensional datasets, there is still room for improvement. Therefore, although quantum computing brings many advantages to fault detection, its implementation in engineering applications still needs to overcome many technical difficulties.

Future work can be devoted to further optimizing the Q-VAE structure and enhancing its adaptability to complex power distribution network fault patterns. Combining with other quantum machine learning algorithms, such as quantum support vector machines and quantum Boltzmann machines, it is expected to further improve the performance of the model. To promote the practical application of quantum computing in fault detection in power distribution networks, it is necessary to carry out large-scale experimental verification in a real power distribution network environment in the future, continuously improve and optimize quantum computing solutions, and promote their widespread application in engineering practice.

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Consent to Publish

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Data Availability Statement

The data that support the findings of this study are available from the corresponding author, upon reasonable request.

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Author Contribution

Zhihai Yan: Developed and planned the study, performed experiments, and interpreted results. Edited and refined the manuscript with a focus on critical intellectual contributions.

Jiali Liu, Xianglong Liu, Xingmeng Yang: Participated in collecting, assessing, and interpreting the data. Made significant contributions to data interpretation and manuscript preparation.

Zhihai Yan, Zaixin Yang: Provided substantial intellectual input during the drafting and revision of the manuscript.

Conflicts of Interest

The authors declare that they have no financial conflicts of interest.

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