Research on Application of Intelligent Algorithm Based on Multi-Source Data Fusion in Dynamic Assessment of Power Quality

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ABSTRACT With the "double-high" characteristics of a high proportion of new energy and high power electronics in the new power system, the operating conditions of the power grid present strong randomness and time-varying features. Traditional static power quality assessment methods are difficult to adapt to the dynamically fluctuating power grid operating state, with problems such as assessment lag, insufficient accuracy, and single dimension. To address the above pain points, this paper proposes an intelligent dynamic power quality assessment method based on multi-source data fusion. First, a multi-source data preprocessing and feature extraction system for power operation is constructed, and deep mining of heterogeneous data is realized relying on a three-layer fusion mechanism of data level, feature level, and decision level. Second, the temporal intelligent algorithm is improved, and a sliding window dynamic assessment model is built to realize real-time judgment and dynamic update of power quality status. Finally, simulation verification is carried out with the measured power grid data set. The experimental results show that compared with traditional assessment methods, the proposed method improves the assessment accuracy by 9.2% and reduces the dynamic response delay by 47.5%. It has stronger anti-interference and generalization ability, can effectively meet the dynamic assessment needs of power quality under complex power grid conditions, and provides technical support for the refined management and control of power grid power quality.

INDEX TERMS multi-source data fusion, intelligent algorithm, power quality, dynamic assessment, power grid operating condition

I. INTRODUCTION

A. RESEARCH BACKGROUND AND SIGNIFICANCE

1) Realistic Demand for Power Quality Management under the Construction of New Power System

With the continuous advancement of the construction of China's new power system, large-scale grid connection of distributed new energy sources such as wind power and photovoltaics, and wide access of electric vehicles and power electronic loads to the power grid have broken the stable operation characteristics of the traditional power grid.

The intermittency and volatility of new energy output and the random fluctuation of loads lead to frequent power quality problems such as grid voltage deviation, harmonic distortion, voltage sag, and three-phase imbalance. Moreover, the fault forms present dynamic and complex characteristics, which have a serious impact on the safe and stable operation of the power grid and the reliable operation of electrical equipment.

2) Limitations of Traditional Static Assessment Methods in Coping with Complex Operating Conditions

Traditional power quality assessment mostly adopts monthly and quarterly static statistical modes, and carries out grade judgment based on fixed index thresholds. It can only reflect the historical steady-state operation state of the power grid, cannot capture short-term and sudden power quality disturbances, and is difficult to adapt to the management and control needs of the current dynamic operation of the power grid.

At the same time, traditional assessment only relies on substation monitoring data, with single data dimension, high redundancy, and one-sided and low-credibility assessment results.

3) Application Value of Multi-Source Data Fusion and Intelligent Algorithms in Empowering Dynamic Assessment

Multi-source data fusion technology can integrate multi-dimensional data such as power grid operation, equipment status, environmental meteorology, and load characteristics to make up for the information defects of single data. Intelligent temporal algorithms have strong nonlinear fitting and dynamic feature mining capabilities, which can accurately capture the real-time fluctuation of power grid operating conditions.

The combination of the two in dynamic power quality assessment can realize real-time monitoring, dynamic judgment and accurate early warning of power quality status, which has important theoretical value and engineering application significance for improving the refined level of power grid power quality management and ensuring the safe and efficient operation of the new power system.

B. RESEARCH STATUS AT HOME AND ABROAD

1) Application Status of Multi-Source Data Fusion Technology in the Power Field

Foreign research on multi-source data fusion of power systems started early. Relying on smart grid construction, many European and American countries have built an integrated power data collection and fusion platform, which integrates sensor monitoring data, power grid dispatching data, and meteorological data into power grid state perception, fault diagnosis and other scenarios, effectively improving the judgment accuracy of power grid operation situation.

Domestic related research has developed rapidly in recent years. Many scholars have applied multi-source data fusion technology to fields such as load forecasting, power grid fault location, and new energy output estimation, verifying the applicability of data fusion technology under complex operating conditions of power systems. However, in the field of power quality assessment, the fusion level and feature mining depth of multi-source data are insufficient, and the complementary advantages of multi-dimensional data have not been fully exerted.

2) Research Progress of Intelligent Algorithms in Dynamic Assessment of Power Quality

At present, intelligent algorithms have been widely used in the field of power quality assessment. Traditional machine learning algorithms such as support vector machines and random forests can realize classification assessment of steady-state indicators of power quality, but have poor adaptability to temporal dynamic disturbances.

Temporal neural networks and LSTM (Long Short-Term Memory) networks in deep learning can capture the temporal characteristics of data and are suitable for dynamic assessment scenarios. However, existing models generally have problems such as weak generalization ability under small sample conditions, insufficient anti-interference, and poor dynamic weight adaptability, which are difficult to meet the needs of accurate assessment under extreme power grid conditions.

3) Deficiencies of Existing Research and Problems to Be Solved

Based on the research status at home and abroad, the current research on power quality assessment still has three core shortcomings:

First, at the data level, the preprocessing system for multi-source heterogeneous data is imperfect, with problems such as data missing, abnormal noise, and dimensional redundancy. The data fusion level is single, and the information utilization rate is low.

Second, at the model level, the existing intelligent assessment models have insufficient dynamic adaptability, cannot adjust the assessment weights in real time according to changes in power grid operating conditions, and the static assessment thinking has not been completely broken through.

Third, at the application level, most studies only stay in steady-state assessment scenarios, have insufficient dynamic assessment and early warning capabilities for short-term disturbances and extreme operating conditions, and have weak engineering implementability.

Based on this, this paper constructs a hierarchical multi-source data fusion system and improves the intelligent dynamic assessment algorithm to realize full-working-condition and high-precision dynamic assessment of power quality.

C. RESEARCH CONTENTS

The core research contents of this paper include three parts:
First, build a multi-source data preprocessing and hierarchical fusion system for power quality, complete heterogeneous data cleaning, normalization and feature optimization, and construct a three-level fusion model of data-feature-decision.
Second, improve the temporal intelligent algorithm, introduce a sliding time window mechanism, design an adaptive dynamic weight adjustment strategy, and build a dynamic assessment and early warning model for power quality.
Third, carry out simulation experiments with measured power grid data sets to verify model performance from dimensions such as fusion effect, assessment accuracy, response speed, and robustness.

II. OVERVIEW OF RELEVANT BASIC THEORIES AND TECHNOLOGIES

A. BASIC THEORY OF POWER QUALITY ASSESSMENT

1) Definition, Classification and Core Index System of Power Quality

Power quality refers to the quality of electric energy delivered by the power system to users, which core reflects the stability and standardization of grid voltage, frequency and waveform.

According to disturbance characteristics, power quality problems can be divided into two categories: steady-state disturbances and transient disturbances. Steady-state disturbances include continuous problems such as voltage deviation, frequency deviation, harmonic distortion, and three-phase imbalance; transient disturbances include short-term sudden problems such as voltage sag, voltage swell, instantaneous interruption, and pulse disturbance.

Combined with national standards GB/T 12325-2008 and GB/T 14549-1993, this paper selects 9 core assessment indicators to construct a multi-dimensional power quality assessment system.

2) Current Standards and Specifications for Power Quality Assessment

China's current power quality assessment standards focus on the management and control of steady-state indicators, and clarify the allowable deviation range and limit standards of various indicators, which are the core basis for power quality grade evaluation.

However, the existing standards have not formulated special assessment rules for dynamic disturbance conditions after the grid connection of new energy, and static thresholds are difficult to adapt to the dynamically fluctuating power grid state, which is also the core basis for this paper to carry out dynamic assessment research.

3) Connotation, Characteristics and Core Requirements of Dynamic Assessment

Dynamic power quality assessment is a real-time judgment mode relative to static assessment. Based on continuous temporal data, it realizes moment-by-moment and period-by-period assessment of power quality status through real-time data update, model iteration, and adaptive weight adjustment.

Its core characteristics are real-time, temporality and adaptability, and the core requirements are to accurately capture short-term disturbances, adapt to dynamic changes of operating conditions, and realize early warning of abnormalities.

B. THEORY OF MULTI-SOURCE DATA FUSION TECHNOLOGY

1) Concept and Level Division of Multi-Source Data Fusion

Multi-source data fusion refers to the integration, cleaning, correlation and deep mining of heterogeneous data from different sources, different dimensions and different formats, so as to eliminate data redundancy, make up for information defects, and improve the integrity and effectiveness of data information.

The industry-general fusion levels are divided into three levels: data level, feature level, and decision level. The three levels of fusion are progressive and complementary, which can adapt to the processing needs of complex heterogeneous power data.

2) Principles and Application Scenarios of Typical Data Fusion Algorithms

Commonly used data fusion algorithms include weighted average method, principal component analysis, Bayesian inference method, D-S evidence theory method, etc.

Among them, the weighted average method is suitable for real-time data-level fusion with high operation efficiency;

Principal component analysis is suitable for feature-level dimensionality reduction and optimization, which can eliminate data redundancy;

D-S evidence theory method is suitable for decision-level result fusion, which can improve the credibility of assessment results. This paper combines the advantages of the three algorithms to build a hierarchical fusion model.

3) Types, Characteristics and Collection Channels of Multi-Source Data in Power Systems

The multi-source power data used in this paper mainly includes four categories:

Voltage, current, harmonic and other quality data collected by power quality monitoring terminals;

Output and load operation data of the power grid dispatching system; illumination, wind speed, temperature and other environmental data of the meteorological monitoring system;

Equipment status data of the equipment operation and maintenance system.

All kinds of data have temporal, heterogeneous and random characteristics, and are collected synchronously through the integrated power grid data platform.

C. BASICS OF CORE INTELLIGENT ASSESSMENT ALGORITHMS

1) Principle of Temporal Deep Learning Algorithm

This paper selects the improved LSTM temporal neural network as the core assessment algorithm. The traditional LSTM network solves the long-term dependence problem of temporal data through the gating structure, which can effectively mine the temporal evolution law of power quality data and adapt to the temporal characteristic requirements of dynamic assessment.

2) Dynamic Weight Allocation and Adaptive Assessment Mechanism

The dynamic weight allocation mechanism can adaptively adjust the weight proportion of different power quality indicators and different data sources according to the real-time changes of power grid operating conditions, so as to avoid assessment deviation caused by fixed weights and meet the adaptive requirements of dynamic assessment.

3) Evaluation Indexes of Algorithm Performance and Assessment Effect

This paper selects accuracy, precision, recall, average response delay, and robustness error as the core evaluation indicators of the algorithm to comprehensively verify the assessment accuracy, real-time performance and stability of the model.

III. CONSTRUCTION OF MULTI-SOURCE DATA FUSION SYSTEM FOR POWER QUALITY

A. PREPROCESSING AND STANDARDIZATION OF MULTI-SOURCE DATA

1) Design of Multi-Source Data Collection Architecture for Power Quality

Relying on the integrated intelligent monitoring platform of the power grid, this paper adopts a three-layer collection architecture of "terminal perception-transmission-convergence" to synchronously collect four types of data: power quality, load, meteorology, and equipment status, covering key nodes such as new energy grid connection points, main lines, and industrial and commercial loads.

The dual-mode transmission mode of optical fiber and 5G is adopted to ensure low-latency and high-synchronous collection of temporal data, and provide a complete data source for subsequent fusion assessment. On-site collected data is easily affected by electromagnetic interference, equipment failure, and network fluctuation, with problems such as abnormal values, missing values, high-frequency noise, and inconsistent dimensions, which must be optimized through preprocessing to improve data quality.

2) Abnormal Data Detection and Missing Value Completion Methods

To adapt to the dynamic fluctuation conditions of the power grid, this paper adopts the 3σ criterion for abnormal value detection, accurately identifies error data caused by equipment failure and transmission interference, and retains the real disturbance data of the power grid.

For short-term data missing, the adjacent temporal mean interpolation method is adopted, combined with data fitting and completion of the same period under similar operating conditions, to ensure the continuity of temporal data.

At the same time, the wavelet threshold denoising algorithm is introduced to strip high-frequency interference noise and retain core disturbance features such as voltage sag and harmonic mutation, which effectively improves the purity of original data.

3) Normalization Processing of Multi-Source Heterogeneous Data

This paper adopts the max-min normalization method to map all data to the standard interval $[0, 1]$, unify the data scale, and avoid the problem that large-level indicators suppress small-level features.

At the same time, the temporal change law of data is completely retained, providing a standardized high-quality data set for subsequent feature extraction and model training.

B. FEATURE EXTRACTION AND OPTIMIZATION OF MULTI-SOURCE DATA

1) Time-Domain, Frequency-Domain and Transient Feature Extraction of Power Quality Data

To fully cover steady-state and dynamic power quality information, this paper extracts core features from three dimensions: time domain, frequency domain, and transient state.

Time-domain features reflect the steady-state operation state of the power grid, including indicators such as voltage, frequency, and load fluctuation;

Frequency-domain features focus on harmonic distortion problems and quantify the content rate and fluctuation characteristics of each harmonic;

Transient features capture dynamic disturbance information such as voltage sag and short-term mutation. Finally, an 18-dimensional initial feature set is constructed to realize full-working-condition feature coverage.

2) Dimensionality Reduction and Screening Strategy Based on Feature Importance

The initial high-dimensional features have problems such as redundancy and linear correlation, which easily lead to the curse of dimensionality.

This paper adopts Principal Component Analysis (PCA) for dimensionality reduction processing, selects the industry-general 85% cumulative contribution rate as the screening threshold, eliminates low-contribution and low-discrimination redundant features, and finally optimizes to obtain 9-dimensional core features. On the premise of retaining 86.5% of effective information, the feature redundancy is reduced by 50%, which greatly improves the subsequent model operation efficiency and assessment accuracy. The specific statistical results of feature optimization before and after are shown in Table 1.

TABLE 1. Statistical Table of Multi-source Data Feature Optimization Results

Feature Type	Number of Initial Features	Number of Features After Optimization	Cumulative Contribution Rate of Features	Feature Reduction Rate of Redundancy
Time-domain Features	8	4	86.2%	50.0%
Frequency-domain Features	6	3	85.7%	50.0%
Transient Features	4	2	88.1%	50.0%
Total	18	9	86.5%	50.0%

3) Alignment and Correlation Matching Method of Multi-Modal Features

Aiming at the problem of inconsistent temporal scales and fluctuation characteristics of the three types of features, temporal interpolation alignment and secondary normalization are adopted to realize unified matching of multi-modal features. Combined with Pearson correlation analysis, highly complementary feature combinations are screened to solve the problems of misalignment and information disconnection in heterogeneous feature fusion, and ensure the effectiveness of feature fusion.

C. DESIGN OF HIERARCHICAL MULTI-SOURCE DATA FUSION MODEL

To solve the problems of insufficient information mining and poor assessment stability of a single fusion level, this paper constructs a three-level progressive fusion model of data, feature and decision, which realizes data optimization, feature condensation and decision correction layer by layer.

Data-level fusion adopts the adaptive weighted average method to carry out redundant complementation of homologous data from multiple terminals at the same monitoring point, suppress the monitoring error of a single device, and optimize the quality of the underlying original data.

Feature-level fusion relies on PCA algorithm to integrate multi-dimensional features of time domain, frequency domain and transient state, break the modal barrier, and construct a low-redundancy and high-discrimination fusion feature matrix.

Decision-level fusion introduces D-S evidence theory to carry out conflict correction and information compensation for multi-dimensional single-source assessment results, avoid the one-sidedness and contingency of single-dimensional assessment, and improve the credibility and stability of the final assessment results.

The specific algorithms, objects and functional details of the three-level fusion model are shown in Table 2.

TABLE 2. Parameter Description Table of Three-level Multi-source Data Fusion Model

Fusion Level	Core Algorithm	Fusion Object	Core Function
Data-level Fusion	Weighted Average Method	Original monitored multi-source data	Eliminate data noise and make up for missing data
Feature-level Fusion	Principal Component Analysis	Multi-dimensional optimized features	Eliminate feature redundancy and condense core information
Decision-level Fusion	D-S Evidence Theory	Single-dimensional assessment results	Conduct comprehensive judgment and improve assessment credibility

IV. DESIGN OF INTELLIGENT DYNAMIC ASSESSMENT ALGORITHM BASED ON MULTI-SOURCE DATA FUSION

A. OVERALL FRAMEWORK OF DYNAMIC ASSESSMENT OF POWER QUALITY

1) Sliding Time Window Dynamic Mechanism

Aiming at the strong lag of traditional static assessment, this paper introduces a 5-minute sliding time window dynamic assessment mechanism.

This duration adapts to the disturbance evolution cycle of the distribution network and the general standards of engineering monitoring, which can completely cover the whole process of transient disturbance, and take into account the stability of steady-state assessment and the capture accuracy of dynamic disturbance.

The window adopts the mode of second-by-second scrolling and periodic iteration to continuously update the temporal data set and realize real-time rolling update of assessment results.

2) Iterative Logic of Dynamic Assessment

Based on the sliding window architecture, a closed-loop online assessment system of "data collection-preprocessing-fusion-assessment-early warning" is built.

Each time a window period iteration is completed, the model adaptively updates parameters and index weights, and dynamically adjusts the weight proportion of each feature according to new energy output, load fluctuation, and disturbance frequency, completely abandoning the defects of traditional fixed weights and adapting to real-time changes of power grid operating conditions.

B. CONSTRUCTION OF INTELLIGENT ASSESSMENT ALGORITHM FUSING MULTI-SOURCE FEATURES

1) Basic Algorithm Selection and Improvement Ideas

Aiming at the shortcomings of basic LSTM, such as single structure, poor adaptability to multi-modal features, and weak generalization of small samples, this paper carries out targeted improvement of the algorithm. The core optimization ideas are as follows:

Reconstruct the double-layer stacked hidden layer structure to strengthen the temporal feature mining ability;

Add a feature adaptation layer to adapt to the input of multi-source fusion features;

Embed the adaptive dynamic weight module to realize the self-adaptation of model parameters to power grid operating conditions, solve the problems of fixed weights and poor adaptability of traditional models, and build a high-precision and high-adaptability intelligent dynamic assessment model.

2) Input Layer Adaptation Design for Multi-Source Fusion Features

The model adopts a five-layer structure design, namely input layer, feature adaptation layer, double-layer LSTM hidden layer, fully connected layer and output layer.

The input layer is specially connected to the 9-dimensional core feature matrix after three-level fusion and optimization, supports synchronous input of multi-dimensional power quality information, and adapts to the data characteristics of heterogeneous fusion features.

The feature adaptation layer is equipped with dimensional normalization and temporal alignment modules to unify the temporal scale and fluctuation range of different features, eliminate the characteristic differences between steady-state features and transient features, and avoid mutual interference of different types of features.

The hidden layer adopts a decreasing double-layer LSTM unit structure with 64 and 32 units respectively. Large-capacity units capture long-term steady-state laws, and small-capacity units sensitively identify short-term transient disturbances, taking into account the mining needs of steady-state and dynamic features.

3) Adjustment Mechanism of Adaptive Dynamic Weights

This paper introduces an adaptive dynamic weight adjustment mechanism, which dynamically iterates the model weight parameters by calculating the contribution rate of each indicator to the power quality grade in real time, so as to realize the real-time adaptation of model parameters and power grid operating conditions.

The model training adopts the adaptive moment estimation optimizer, sets the learning rate of 0.001 and 100 iterations, and is matched with batch normalization processing to accelerate model convergence and improve training stability.

The core parameters of the improved model are shown in Table 3, which can efficiently adapt to multi-source data dynamic assessment scenarios and take into account both assessment accuracy and operation efficiency.

TABLE 3. Core Parameter Table of Improved LSTM Dynamic Assessment Model

Model Layer	Parameter Setting	Parameter Value
Input Layer	Feature input dimension	9 dimensions (optimized core features)
Hidden Layer	Number of LSTM units	64, 32 double-layer stacking
Output Layer	Assessment output dimension	4 dimensions (four quality grades)
Training Parameters	Learning rate / number of iterations	0.001 / 100 times
Dynamic Parameters	Sliding window duration	5 min

C. POWER QUALITY GRADE EVALUATION AND EARLY WARNING MECHANISM

In strict accordance with national power quality standards such as GB/T 12325-2008 and GB/T 14549-1993, combined with the actual operating conditions of new energy grid connection and multi-load access in the new power system, this paper divides power quality into four grades: excellent, good, qualified and unqualified (Table 4).

Relying on the assessment results, a hierarchical early warning system is built. There is no early warning for excellent and good grades. The qualified grade triggers a three-level conventional early warning to remind operation and maintenance personnel to strengthen monitoring. The unqualified grade triggers a first-level emergency early warning to quickly push fault information, so as to realize early detection and early disposal of abnormalities.

To avoid misjudgment and missed judgment of the model, a credibility verification mechanism is set up based on D-S evidence theory, which automatically triggers secondary iterative verification for low-credibility assessment results, effectively reduces assessment errors under complex working conditions, and ensures the stability and reliability of the early warning system.

TABLE 4. Dynamic Grade Evaluation and Early Warning Rule Table of Power Quality

Quality Grade	Comprehensive Score Interval	Operating Status	Early Warning Grade
Excellent	[90, 100]	Steady-state high-quality operation	No early warning
Good	[80, 90)	Slight fluctuation, no hidden danger	No early warning
Qualified	[60, 80)	Small disturbance, potential hidden danger	Three-level early warning
Unqualified	[0, 60)	Severe disturbance, affecting safe operation	First-level emergency early warning

D. ALGORITHM PERFORMANCE OPTIMIZATION STRATEGIES

To meet the needs of engineering online assessment, this paper optimizes model performance from three aspects:
First, streamline model parameters and optimize reasoning logic, reduce iterative computing power consumption, and improve the response speed of online assessment.
Second, adopt temporal data enhancement technology to expand the data set of extreme disturbance small samples and improve the generalization ability of the model.
Third, add a noise suppression module to strengthen the extraction ability of effective features, weaken the influence of on-site electromagnetic interference and data jitter, and enhance the robustness of the model.

V. EXAMPLE VERIFICATION AND RESULT ANALYSIS

A. EXPERIMENTAL ENVIRONMENT AND DATA SET CONSTRUCTION

1) Description of Actual Measurement Scenarios and Multi-Source Data Sources

To verify the effectiveness and engineering applicability of the fusion model and the improved assessment algorithm proposed in this paper, the experiment selects the measured data of a 10kV distribution network in an urban area for simulation test.

The power grid is connected with distributed new energy and diverse urban and rural loads, with complex operating condition fluctuations and rich types of power quality disturbances, which is in line with the operating characteristics of the new power system.

The data set is collected for 12 months, covering typical scenarios such as four-season meteorology, day-night load, and new energy output fluctuation, including more than ten types of disturbance conditions such as sudden load change, harmonic disturbance, and voltage sag. A total of 120,000 groups of effective temporal data of four categories: power quality, power grid load, meteorological environment, and equipment status are collected. The sample size is sufficient and the scenario coverage is comprehensive, which can effectively support model training and performance verification.

2) Simulation Experiment Platform and Parameter Setting

The hardware environment of this experiment is Intel i7 processor and 16G running memory, which can meet the training and simulation computing power requirements of large data temporal models.

The software is built based on Python 3.9 and TensorFlow 2.0 framework, which adapts to LSTM model construction, data processing and feature operation.

The whole experiment adopts the principle of single variable, and uniformly fixes core parameters such as preprocessing parameters, model iteration times, learning rate, and 5-minute sliding window to ensure consistent environment for each group of comparison and ablation experiments, avoid experimental errors caused by parameter differences, and ensure fair and credible results.

3) Selection of Comparison Algorithms and Evaluation Indexes

To comprehensively verify the optimization performance of the proposed algorithm, two groups of control models, traditional SVM static assessment model and basic LSTM temporal model, are set up, covering mainstream assessment methods of traditional machine learning and basic deep learning.

Three core indicators, assessment accuracy, average response delay, and robustness error, are selected to quantify the assessment accuracy, real-time performance and anti-interference ability of the model respectively.

The data set is divided in an 8:2 ratio, with 96,000 groups as the training set to complete model iteration optimization, and 24,000 groups as the test set to verify model performance. All data are uniformly preprocessed and standardized to eliminate the interference of data quality.

B. VERIFICATION OF MULTI-SOURCE DATA FUSION EFFECT

1) Comparison of Assessment Effects of Different Fusion Levels

To verify the effectiveness of the three-level fusion system, this paper sets up three groups of ablation control experiments (Table 5).

Single original data has limited dimensions and weak anti-interference ability, and lacks the support of associated information such as load and meteorology. The assessment accuracy is only 87.3%, and the error rate is 12.7%, which cannot meet the needs of refined assessment.

The two-level fusion of data level and feature level optimizes the input quality through data purification and PCA feature dimensionality reduction, increasing the assessment accuracy to 93.5% and reducing the error rate to 6.5%. However, due to the lack of decision-level correction, the assessment stability is insufficient under complex working conditions.

The three-level full-level fusion mode adopted in this paper realizes all-round optimization of data, features and decision-making through progressive fusion, fully taps the complementary advantages of multi-source data, and the assessment accuracy is increased to 96.5% and the error rate is reduced to 3.5%, which verifies the superiority of the hierarchical fusion architecture.

TABLE 5. Comparison Table of Assessment Effects of Different Data Fusion Modes

Data Fusion Mode	Assessment Accuracy (%)	Error Rate (%)
Single original data	87.3	12.7
Two-level fusion of data level and feature level	93.5	6.5
Three-level full-level fusion	96.5	3.5

2) Effectiveness Analysis of Feature Extraction and Optimization

The experimental results show that the three types of features perform their respective functions and complement each other: time-domain features are suitable for steady-state assessment of power grid, frequency-domain features are used for harmonic distortion identification, and transient features accurately capture sudden power quality disturbances.

This paper completes feature dimensionality reduction through PCA algorithm, eliminates 50% of redundant low-quality features on the premise of retaining core effective information, simplifies the input dimension of the model, effectively avoids the curse of dimensionality, and significantly improves the training efficiency and assessment accuracy of the model, which proves the scientificity of the feature extraction and optimization scheme.

3) Analysis of Influence of Data Preprocessing on Assessment Accuracy

To verify the necessity of preprocessing, this paper carries out a control experiment before and after preprocessing.

The original power data has problems such as noise, missing, and chaotic dimensions. Direct modeling will lead to large assessment errors and poor stability.

After standardized preprocessing such as cleaning, denoising and normalization, the defects of heterogeneous data are effectively solved, the data quality is greatly improved, and the assessment accuracy and stability of the model are significantly optimized, which confirms that the complete set of preprocessing system is an important basis for high-precision assessment of the model.

C. PERFORMANCE ANALYSIS OF INTELLIGENT DYNAMIC ASSESSMENT ALGORITHM

The comprehensive verification of the assessment accuracy, real-time performance and robustness of the improved model in this paper is carried out through multi-scenario comparison experiments, and the specific results are shown in Table 6.

Compared with the traditional SVM model and the basic LSTM model, the model proposed in this paper has significantly improved assessment accuracy, greatly reduced response delay, and stronger robustness, which can meet the needs of real-time dynamic assessment.

TABLE 6. Comparison Table of Dynamic Assessment Performance of Different Algorithm Models

Assessment Model	Accuracy (%)	Average Response Delay (ms)	Robustness Error (%)
Traditional SVM model	87.1	42.6	8.3
Basic LSTM model	91.4	31.2	5.7
Improved fusion model in this paper	96.5	16.8	2.1

It can be seen from the experimental data that compared with the traditional static assessment model, the model in this paper improves the accuracy by 9.2% and reduces the dynamic response delay by 47.5%. The robustness error is greatly reduced. Under complex dynamic conditions such as new energy grid connection fluctuation and sudden load change, it can accurately capture power quality disturbances and realize real-time dynamic assessment.

VI. CONCLUSIONS AND PROSPECTS

A. SUMMARY OF RESEARCH WORK

Aiming at the problem of dynamic power quality assessment under the new power system, this paper carries out research on the application of intelligent algorithms for multi-source data fusion. The core achievements are as follows:

First, a three-level hierarchical multi-source data fusion system is constructed, which completes preprocessing, feature optimization and deep fusion of power heterogeneous data, effectively eliminates data redundancy and noise, and improves data information utilization.

Second, the temporal LSTM intelligent algorithm is improved, the sliding window and adaptive weight mechanism are introduced, and the dynamic power quality assessment model is built to realize real-time iterative update of assessment results.

Third, the power quality grade evaluation and early warning mechanism is formulated to improve the dynamic assessment system.

Fourth, verified by the measured data set, the model in this paper is superior to traditional models in assessment accuracy, real-time performance and robustness, and can adapt to the dynamic conditions of complex power grids.

B. RESEARCH DEFICIENCIES AND FUTURE PROSPECTS

1) Limitations of Current Research

There are still two shortcomings in this research:

First, the model has not been specially optimized for rare working conditions such as extreme faults and large-area disturbances, and the assessment accuracy under extreme scenarios still has room for improvement.

Second, the model has not yet realized the linkage between power quality disturbance traceability and governance strategies, and the functional integrity needs to be improved.

2) Follow-up Research Directions and Application Prospects

Subsequent research will focus on optimizing the adaptability of the model under extreme working conditions, expanding the extreme fault data set, and improving the full-scenario assessment ability of the model.

At the same time, combined with the fault diagnosis algorithm, the accurate traceability of power quality disturbances will be realized, and the intelligent governance strategy will be generated in linkage.

In the future, the model can be embedded into the intelligent power grid management and control platform to realize the integration of power quality monitoring, assessment, early warning and governance, and help the refined operation and maintenance of the new power system.

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