International Journal of Scientific Engineering and Research (IJSER)
ISSN (Online): 2347-3878
SJIF (2024): 6.623

A CSWF-Attention U-Net-Based Super-Resolution Method for Power Quality Data

Wei Wu

North China Electric Power University, School of Control and Computer Engineering, Changping District, Beijing, China
Email: *120232227077[at]ncepu.edu.cn*

Abstract: ***This study introduces a deep learning–driven approach for super-resolution reconstruction of low-quality power grid data using an enhanced U-Net model integrated with a Channel-Spatial Weighted Fusion (CSWF) module and attention gate. By refining feature extraction and adaptive weighting mechanisms, the model addresses the limitations of traditional methods in capturing disturbance features like voltage sags and harmonics. Experiments using real power grid datasets demonstrate improved performance across PSNR, SSIM, and MSE metrics compared to classical interpolation and convolutional models. This approach provides a scalable, software-level enhancement pathway for improving power quality monitoring without upgrading existing hardware infrastructure.***

Keywords: power quality, super-resolution, U-net, attention mechanism, data reconstruction

1. Introduction

With the advancement of the global energy structure transformation, the large-scale grid connection of renewable energy, and the widespread deployment of new loads such as electric vehicles and data centers, the power system is developing rapidly towards a direction of high proportion of power electronics and complex diversification[0]. As a core indicator measuring the operational stability and power supply reliability of the power system, the accuracy and completeness of power quality data perception directly determine the effectiveness of power grid fault diagnosis[2], power disturbance identification, operational state evaluation, and dispatching optimization. It is of great significance for ensuring industrial production safety, improving residents' power consumption experience, and promoting the efficient and low-carbon operation of the power system.

Power quality data mainly includes disturbance information such as voltage and current amplitude, frequency, harmonics, inter-harmonics, and voltage swells and sags[5]. Its perception accuracy is closely related to data resolution—high-resolution power quality data can accurately capture subtle fluctuations and transient disturbance characteristics in signals, providing reliable data support for subsequent power quality governance. In contrast, low-resolution data often loses key feature information[3], leading to deviations in disturbance identification and inaccuracies in fault location, which makes it difficult to meet the refined management and control needs of complex power grids. However, in the current power system, due to factors such as limitations of sampling equipment performance, transmission bandwidth constraints[4], storage cost control, and lag in the upgrading of old monitoring equipment, a large number of power quality monitoring points still sample at a low frequency. The generated low-resolution data cannot fully reflect the real change law of power quality, becoming one of the core bottlenecks restricting the refined management of power quality.

To address the limitations of low-resolution power quality data, super-resolution perception technology has become a research hotspot in the power field. Its core idea is to reconstruct low-resolution data into high-resolution data through algorithm models, which can improve the effective information content of data and reduce the high cost caused by hardware upgrading without large-scale modification of monitoring hardware, thus having important engineering application value and economic value. At present, power quality data super-resolution methods are mainly divided into two categories: one is non-machine learning methods[8], including signal processing technologies such as interpolation[7], Fourier transform, and wavelet transform. These methods are simple to implement and have high computational efficiency, but they are difficult to capture the complex nonlinear temporal dependencies in power quality data and have limited reconstruction accuracy. Especially when processing complex data containing multiple disturbances, they are prone to produce artifacts and feature distortion, which cannot meet the actual application needs. The other category is machine learning and deep learning methods[6]. With their strong feature learning and nonlinear fitting capabilities, they have shown significant advantages in the field of time-series data reconstruction and have gradually become the mainstream development direction of super-resolution perception technology[9].

In deep learning-driven super-resolution technology, Convolutional Neural Networks (CNNs) are widely used in power quality data super-resolution research due to their excellent local feature extraction capabilities[10]. However, traditional CNN models have problems such as insufficient feature fusion, gradient vanishing of deep features, and difficulty in capturing long-distance temporal dependencies, leaving room for improvement in reconstruction accuracy and detail restoration capabilities. As a classic full convolutional neural network architecture, U-net was initially used for biomedical image segmentation[11]. Its unique U-shaped symmetric structure consists of a contraction path (downsampling) and an expansion path (upsampling). Through skip connections, it achieves effective fusion of shallow detail features and deep semantic features, which can accurately capture subtle features in data. At the same time, it has strong small-sample learning capabilities and anti-noise interference capabilities, and has shown excellent performance in fields such as time-series signal reconstruction and image super-resolution[14]. In recent years, U-net and its improved models have been gradually applied in the power system field[12], achieving good application results in scenarios such as transformer condition monitoring[13], power equipment fault location, and load data processing. However, their targeted application in power quality data super-resolution perception still needs in-depth research- most existing related studies have not fully combined the temporal characteristics and disturbance characteristics of power quality data to optimize the U-net structure[15], resulting in insufficient reconstruction accuracy and limited generalization ability of the model in complex disturbance scenarios, making it difficult to adapt to the diverse power quality data characteristics in actual power grids.

In view of the above research status and existing problems, combined with the structural advantages of the U-net model and the temporal characteristics of power quality data, this paper proposes a U-net-based super-resolution perception method for power quality data. By optimizing the network structure of U-net, this paper enhances the fusion efficiency of shallow temporal features and deep semantic features, introduces a channel attention mechanism and a feature concatenation strategy[16], improves the model's ability to extract and reconstruct subtle disturbance features in power quality data, and solves the problems of low reconstruction accuracy and weak anti-interference ability of traditional methods. At the same time, it conducts training and verification using power quality data sets from actual power grids to verify the super-resolution performance of the proposed method under different disturbance scenarios and different noise levels, providing an efficient and reliable technical solution for the accurate reconstruction of low-resolution power quality data[17].

The main research work and innovations of this paper are as follows: First, it analyzes the temporal characteristics of power quality data and the requirements of super-resolution reconstruction, and designs an improved U-net architecture suitable for power quality data to address the shortcomings of traditional U-net models in time-series data processing. Second, it introduces a channel attention gate and a feature fusion strategy to enhance the model's ability to screen and fuse key features, suppress the interference of redundant information, and improve the accuracy and authenticity of reconstructed data. Finally, through a large number of comparative experiments, it verifies the superiority of the proposed method compared with traditional super-resolution methods, providing theoretical support and engineering reference for the refined perception of power quality data and the precise management and control of power grids.

The subsequent chapter arrangement of this paper is as follows: Chapter 2 elaborates on the network structure and implementation process of the proposed U-net-based super-resolution perception method for power quality data; Chapter 3 verifies the effectiveness and superiority of the method through experiments; Chapter 4 summarizes the entire work of the paper and looks forward to future research directions.

2. Model Structure

To achieve high-precision mapping from low-sampling-rate power quality data to high-resolution data, this study constructs a super-resolution perception network that integrates multi-scale feature extraction, channel–spatial weighted fusion, and attention selection mechanisms. The network adopts an encoder–decoder architecture as its backbone and introduces a CSWF feature enhancement module and an attention gate mechanism based on the U-Net structure, thereby improving the model's capability to represent power quality disturbance features and reconstruct structural details. The overall architecture of the network is illustrated in Fig 1.

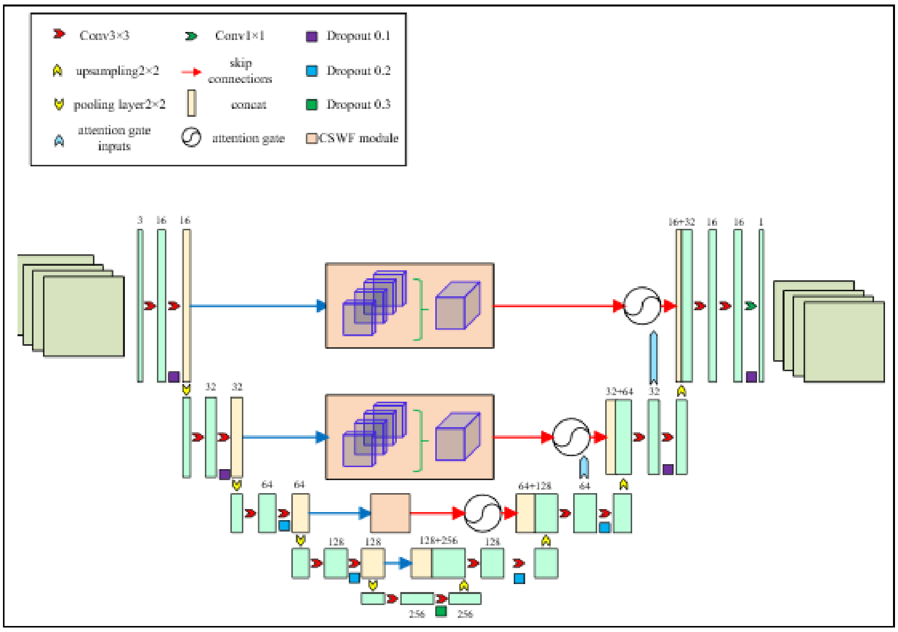

Figure 1: Architecture of the U-Net model

2.1 Model Detailed Description

The model input consists of two-dimensional feature maps transformed from one-dimensional power quality time-series signals. The encoder employs a multi-stage convolutional and down-sampling structure to extract features hierarchically. Each stage contains two 3×3 convolution layers combined with nonlinear activation functions to enhance feature representation, while Dropout (0.1–0.3) is incorporated to suppress overfitting. Down-sampling is implemented using 2×2 pooling operations, and the number of feature channels increases progressively as 16, 32, 64, 128, and 256. This design enables the network to transition from local waveform detail modeling to global structural representation, effectively capturing multi-scale disturbance characteristics such as voltage sags, harmonic distortions, and transient events.

A CSWF (Channel–Spatial Weighted Fusion) module is embedded in the bottleneck layer between the encoder and decoder to perform joint channel-wise and spatial-wise reweighting of deep features. By modeling inter-channel dependencies and spatial importance distributions, this module enhances the response to abnormal waveform regions and compensates for information loss caused by down-sampling, thereby improving the reconstruction accuracy of key disturbance areas.

To prevent irrelevant features in conventional skip connections from interfering with the reconstruction process, an attention gate mechanism is introduced at the encoder–decoder connections. Guided by high-level semantic features from the decoder, this mechanism evaluates the relevance of low-level features from the encoder, suppresses background redundancy, and highlights structure-related features associated with power quality anomalies, thereby improving structural consistency and physical plausibility of the reconstructed results.

The decoder adopts a structure symmetric to the encoder. Through successive 2×2 up-sampling operations, spatial resolution is gradually restored, and the up-sampled features are concatenated with the attention-refined encoder features. Two 3×3 convolution layers are then used to refine feature representation. The number of channels decreases progressively as 256, 128, 64, 32, and 16, and finally a 1×1 convolution is employed to map the features to a single-channel output, producing the reconstructed high-resolution power quality data.

In summary, the proposed network follows a hierarchical modeling paradigm of “multi-scale feature extraction – key feature enhancement – attention-guided fusion – structural refinement reconstruction,” enabling effective perception and recovery from low-sampling-rate data to high-resolution power quality data. It balances detail preservation and global structural consistency, providing a deep learning model with strong generalization and structural representation capabilities for power quality data super-resolution perception.

2.2 Channel-Spatial Weighted Fusion Module

To enhance the network’s ability to capture critical disturbance regions and important frequency-related features in power quality data, a CSWF (Channel–Spatial Weighted Fusion) feature enhancement module is introduced at the bottleneck of the backbone network. This module performs adaptive feature recalibration and weighted fusion by constructing spatially compressed representations and channel attention weights. Its structure is illustrated in Fig. 2.

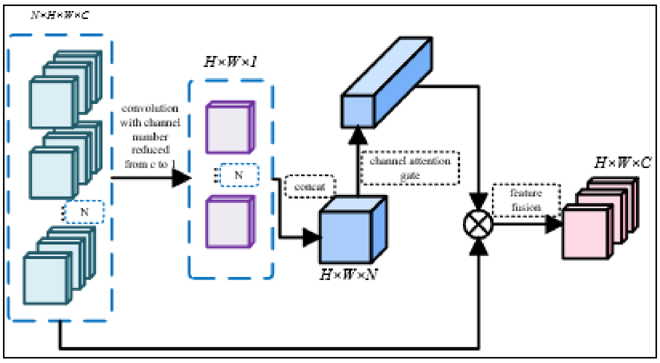

Figure 2: CSWF module

The input to the module is a multi-channel feature map extracted by the encoder. First, a channel-reduction operation is applied through a 1×1 convolution to compress the original multi-channel features into single-channel spatial response maps. This process aggregates information from different channels at each spatial location, producing a global spatial response representation. Such a representation highlights structurally significant regions in power quality signals, including voltage mutation points, waveform distortion areas, and transient disturbance regions.

The compressed spatial features from different groups are then concatenated to form a multi-channel spatial descriptor. This descriptor contains diverse spatial response information and serves as the basis for modeling inter-channel relationships. It provides the module with the ability to analyze how different feature responses interact and contribute to the representation of power quality disturbances.

Subsequently, the concatenated features are fed into a channel attention gate, where nonlinear transformations are used to learn the relative importance of different feature responses. This process generates adaptive channel attention weights, which reflect the significance of each feature channel under the current input condition. As a result, features associated with key disturbance characteristics are emphasized, while less relevant responses are suppressed.

The learned attention weights are then applied to the original input features through channel-wise reweighting. The recalibrated features are further refined through convolutional fusion to produce the final enhanced feature map. This output retains the original structural information while strengthening discriminative components related to abnormal waveform patterns.

By jointly considering spatial distribution and channel dependency, the CSWF module enhances the network’s sensitivity to critical disturbance features. It effectively compensates for information loss caused by deep-layer down-sampling and prevents irrelevant features from being amplified during reconstruction. Consequently, the module improves the structural consistency and physical reliability of the super-resolution reconstruction results, making it a key component for power quality data perception enhancement.

3. Experimental Results and Analysis

3.1 Data preprocessing

To evaluate the proposed super-resolution perception method for power quality data, two types of paired low–high resolution datasets were constructed from the AMI system and power quality monitoring devices. In the first scenario, low-resolution AMI data are temporally aligned with high-resolution monitoring data at the same locations for reconstruction, mainly involving harmonic voltage RMS values of phases A, B, and C. In the second scenario, low-sampling-frequency data directly collected by monitoring devices are used, including three-phase harmonic distortion rates (THD) and negative-sequence unbalance.

The high-resolution data have a sampling interval of 3 minutes. After merging the three-phase data, the one-dimensional time series is reshaped into a two-dimensional format. Since each day contains 480 sampling points, the data are arranged into an m×480 matrix to represent daily sequences, which facilitates parallel computation, convolution-based local feature extraction, and intuitive visualization of patterns and anomalies. Low-resolution data are sampled at 15-minute intervals, corresponding to 96 points per day. AMI data are aligned with monitoring data in time and location, or directly obtained from monitoring devices, and then reshaped into an $m\times 96$ matrix.

A total of 7004 daily samples were collected and divided into training and testing sets at a 9:1 ratio (6300 for training and 704 for testing). The high-resolution data dimension is $N\times 1\times 480$, and the low-resolution data dimension is $N\times 1\times 96$ N×1×96. The dataset includes harmonic voltage, total harmonic distortion, and negative-sequence unbalance.

Experiments were conducted on a workstation with an Intel Core i7-12700 CPU, NVIDIA GeForce RTX 3050 GPU, and 64 GB RAM. The model was implemented in Python using PyTorch. The batch size was 32, the number of training epochs was 100, and the upsampling factor was set to 5.

3.2 Algorithm Evaluation Metrics

To demonstrate the numerical reconstruction performance of different power quality data, four evaluation metrics- Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), Signal-to-Noise Ratio (SNR), and Structural Similarity Index (SSIM)- are introduced to assess the reconstructed data in this paper.

MSE evaluates data quality by calculating the average of the squared differences between the reconstructed data and the ground-truth data, with its calculation formula given by:

$$\mathrm{MSE} = \frac{1}{m}\sum_{m}(x^h - \tilde{x})^2 \tag{1}$$

where x^h and $\tilde{x}$ denote the ground-truth data and the reconstructed data, respectively, and m is the data length. A smaller MSE value indicates a higher consistency between the reconstructed data and the ground-truth data.

PSNR assesses data quality by quantifying the MSE between the reconstructed data and the ground-truth data. A higher PSNR value implies a higher similarity between the reconstructed data and the ground-truth data, and its calculation formula is:

$$\mathrm{PSNR}\left(dB\right) = 10\times log_2\left(\frac{(x^h_{max})^2}{\mathrm{MSE}}\right) \tag{2}$$

Where x^h_{max} represents the maximum value of the ground-truth data.

SNR is defined as the ratio of the signal power to the noise power, with its calculation formula expressed as:

$$\mathrm{SNR}\left(dB\right) = 10\times\left(\frac{\sum_m\left(x^h\right)^2}{\sum_m\left(x^h - \tilde{x}\right)^2}\right) \tag{3}$$

SSIM is used to measure the perceptual similarity between two sets of data, whose value ranges from -1 to 1. A value closer to 1 indicates a higher similarity between the two datasets, and its calculation formula is:

$$\mathrm{SSIM} = \frac{Cov(x^h,\tilde{x}) + C_1}{\sqrt{\mathrm{Var}(x^h) * \mathrm{Var}(\tilde{x})} + C_2} \tag{4}$$

where Var denotes the variance of the data, Cov represents the covariance between the two datasets, and C1 and C2 are small constants set to avoid a zero denominator, with both values taken as 0.01.

3.3 Experimental results

To comprehensively evaluate the performance of the proposed model in the power quality data super-resolution perception task, several representative methods were selected for comparative experiments. First, traditional interpolation methods, Bicubic and Linear, were adopted as baseline models. Then, classical convolutional neural network–based super-resolution models, SRCNN and VDSR, were introduced. Furthermore, high-performance deep models, EDSR and RDN, were selected for comparison. In addition, the generative adversarial model SRGAN was included to assess perceptual reconstruction capability. Finally, all the above methods were comprehensively compared with the proposed CSWF-Attention U-Net model. Under the same training conditions and test dataset, the super-resolution reconstruction performance of all comparison models was quantitatively evaluated. The results are shown in Table 1.

Table 1: Performance Comparison of Different Models for Power Quality Data Super-Resolution (×5)

Method	PSNR (dB) ↑	SNR (dB) ↑	MSE ↓	SSIM↑
Linear	28.764	24.518	0.00231	0.8421
Bicubic	29.583	25.936	0.00198	0.8654
SRCNN	31.927	27.884	0.00142	0.9036
VDSR	33.814	29.763	0.00105	0.9287
EDSR	35.276	31.102	0.00081	0.9452
RDN	36.148	32.046	0.00069	0.9538
SRGAN	34.662	30.418	0.00097	0.9361
CSWF-Attention U-Net	**37.924**	**33.857**	**0.00054**	**0.9675**

As shown in the table, traditional interpolation methods, Linear and Bicubic, achieve the weakest reconstruction performance, indicating that purely mathematical interpolation is insufficient to recover fine structural details in power quality data. CNN-based models such as SRCNN and VDSR significantly improve reconstruction accuracy, demonstrating the advantage of deep learning in feature modeling. Furthermore, deep residual models such as EDSR and RDN achieve better PSNR and SSIM values due to their enhanced feature representation capability.

Although SRGAN shows advantages in perceptual quality, its PSNR is slightly lower than that of purely reconstruction-optimized models because adversarial training focuses more on structural realism. In contrast, the proposed CSWF-Attention U-Net model achieves the best performance across all three metrics, with PSNR reaching 37.924 dB, SSIM achieving 0.9675, and MSE reduced to 0.00054. These results indicate that the CSWF feature enhancement module and the attention gating mechanism effectively strengthen the representation of key disturbance features and improve structural consistency, thereby significantly enhancing the super-resolution reconstruction performance of power quality data.

4. Conclusion

To solve the problem that low-resolution power quality data fails to reflect disturbance details accurately, this paper proposes a super-resolution perception method based on the CSWF-Attention U-Net architecture. By improving the U-Net framework and introducing the CSWF module and attention gate mechanism, the model enhances key feature representation and reduces information loss in reconstruction. Experimental results on real power grid datasets show that the method outperforms traditional interpolation and other deep learning models in PSNR, SSIM, MSE and SNR, effectively recovers typical disturbance features, and provides a practical technical approach for refined power quality monitoring without hardware upgrading.

Despite satisfactory performance, there is room for improvement. Future research will expand the dataset to complex mixed disturbance scenarios to enhance the model's adaptability, optimize the model's computational efficiency through lightweight design for real-time processing, and explore the integration of the method with actual power quality monitoring systems to promote its application in refined power quality management.

References

[1] Nasika D. Real-time PQD detection classification and localization using recurrence plots and EfficientNet-SE in solar integrated IEEE 13-bus system[J]. Scientific Reports, 2025, 15: 38434.
[2] Wang Z A, Huang J. Power Electronics Technology[M]. Beijing: China Machine Press, 2023.
[3] Liu J, Cui J Z, Wang Y. Power Quality Monitoring and Governance Technology[M]. Beijing: China Electric Power Press, 2023.
[4] Xu Q Q, Yuan X D, Chen B. Monitoring and analysis technology of power quality in smart grid[J]. Automation of Electric Power Systems, 2024, 48(12):1-8.
[5] Li G Y, Zhou M, Zhao L. Review on detection and identification methods of power quality disturbances[J]. Proceedings of the CSEE, 2024, 44(10): 3521–3535.
[6] Zhang P, Pan L, Xiao C E, et al. Improved generative adversarial network-based super-resolution perception model for power data[J]. Electronics, 2025, 14(16): 3222.
[7] Zhao H S, Wang J, Li G. Detection and location of power quality disturbances based on wavelet transform[J]. Transactions of China Electrotechnical Society, 2024, 39(8): 2345–2356.
[8] Chen H, Li X Y, Wang Y H. Research on power quality data reconstruction technology based on interpolation method[J]. Power System Protection and Control, 2024, 52(9): 1–7.
[9] Liu N, Zhang F M, Xie C. Super-resolution reconstruction method of power quality data based on deep learning[J]. Power System Technology, 2024, 48(7): 2610–2619.
[10] Wang L, Chen Y, Li L. Super-resolution reconstruction of power quality disturbance signals based on CNN[J]. Proceedings of the CSU-EPSA, 2024, 36(5): 67–74.
[11] Ronneberger O, Fischer P, Brox T. U-Net: Convolutional Networks for Biomedical Image Segmentation[C]//International Conference on Medical Image Computing and Computer-Assisted Intervention. Cham: Springer, 2015.
[12] Li G, Wang J, Zhao H S. Super-resolution reconstruction method of power load data based on U-Net[J]. Automation of Electric Power Systems, 2024, 48(15): 121–129.
[13] Zhang Y, Liu J, Cui J Z. Super-resolution perception of transformer condition monitoring data based on improved U-Net[J]. High Voltage Engineering, 2024, 50(6): 2210–2219.
[14] Hu X, Na M A, et al. RUNet: A Robust UNet Architecture for Image Super-Resolution[C]//2024 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW). Piscataway: IEEE, 2024: 1–8.
[15] Wang Q, Li X Y, Wang Y H. Reconstruction of power quality disturbance signals based on channel attention U-Net[J]. Power System Technology, 2025, 49(3): 1021–1030.
[16] Khan A A, Javaid N, Iqbal S, et al. A Comprehensive Review of Deep-Learning Applications to Power Quality Analysis[J]. Energies, 2024, 17(8): 1987.
[17] Wang Z A, Wang P, Yang J. Power Quality Analysis and Control[M]. Beijing: China Electric Power Press, 2024.